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Optimization of Hybrid Propulsion Systems

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ABSTRACT: Powertrain hybridization permits the benefits of more than one power source to be integrated and exploited for a beneficial effect on an objective, such as reduction of fuel consumption or emissions. Due to their operating profiles however, marine hybrid vessels do not exhibit much opportunity for free energy recuperation. Fuel savings can be realized by bettering component operating points, yet this requires correct sizing matched to the expected usage. In this paper, a multi-objective genetic algorithm is used to optimally size propulsion components in order to minimize fuel consumption as well as installation weight for a hybrid motoryacht operating on a day cruise scenario.

1 INTRODUCTION

Hybrid vehicles are now well established on land as a viable mode of greener transportation. The use of multiple energy sources and converters permits their individual benefits to be better utilized, by exploiting the inherent disparity between peak and average power demands (Schofield et al. 2005).

At sea, powertrain hybridization would equally permit the power demand to be met more effectively than by a single source. Yet marine hybrids are still not as popular as on land. 'Conventional' hybrids on marine vessels include diesel-electric systems, popular on passenger vessels, as well as CODLAG systems found on naval vessels. Such configurations of parallel electric and mechanical propulsors permit better efficiencies at part-loading and low speeds, due to the different sources being better suited for different loadings (Woud & Stapersma 2002). These hybrids however, differ from automotive ones in that they lack an Energy Storage System (ESS), typically in the form of chemical batteries.

The inclusion of an ESS would permit the loading of the prime movers to be optimized for greater periods of time, by using the ESS as a load bank during periods of low propulsion demand. Compared with automotive vehicles however, propulsive power demands for marine vessels are significantly larger; hence, by proportional scaling, the corresponding ESS would be excessively large, with an associated cost and weight factor.

The major shortcoming for marine hybrids stems from a lack of significant regenerative capability. A significant proportion of the energy efficiency for automotive hybrids comes from regenerative braking (Lukic et al. 2008). This permits energy which would otherwise be dissipated as heat at the brakes to be recovered to recharge the ESS. However, the lack of stop signs and traffic lights at sea much reduces the scope for energy recovery from deceleration. This is most apparent when comparing typical demand profiles between the New European Driving Cycle (a European standardized profile) representing a typical automotive suburban commute, and a typical day cruise for a marine vessel (Figure 1).

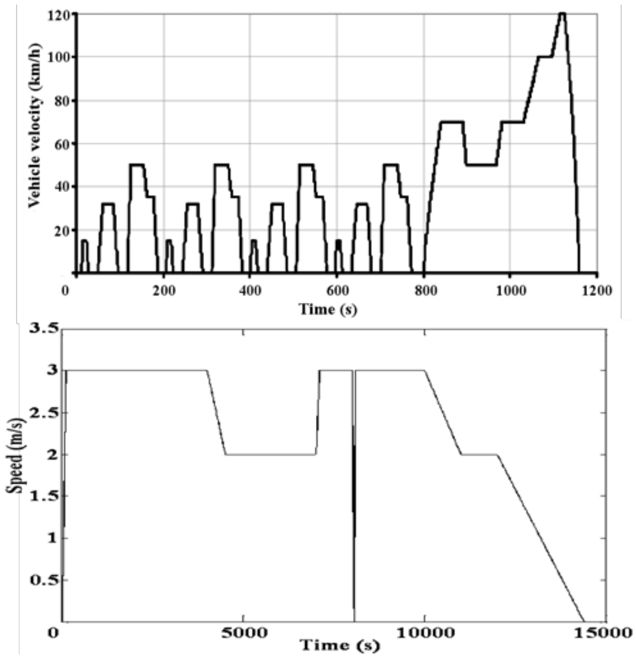

Figure 1. Comparison of automotive (top) and marine vessel (bottom) propulsion timelines (Barabino et al. 2009).

Fuel savings in the case of a marine hybrid are hence possible through correct sizing of components, such that overall operating points are improved over a particular scenario. Defining the fuel consumption for a scenario therefore requires a model for the hybrid system, which takes the scenario power demand as its input.

2 MODELLING

The optimal sizing of the hybrid system is simply the tip of the iceberg in the hybrid design process. Essential for the correct sizing is the demand profile, on whose realism the accuracy of the sizing will depend.

The power demand timeline for a marine hybrid consists of two parts, namely the propulsion demand and the hotel load demand. Also differing from automotive hybrids is a more significant hotel load, since motoryachts generally need to support onboard users for longer periods.

In determining the fuel consumption, consideration must be given to the interaction between prime mover, ESS and power demands. This requires a complete model of the hybrid system which considers all the power flows between the various components.

This model was built in Simulink, since no simulation tool was readily available for marine vessels. A sixty foot motoryacht was considered, for which trials data was available. A parallel hybrid configuration was proposed for this existing boat, by the addition of a battery bank and an electric motor/generator coupled to each diesel engine by a gearbox. The separate diesel generator could then be omitted by supplying the hotel load from the main battery bank and main engines.

From the trials data, the propulsive power demands were input as a Look-Up Table (LUT), returning the demanded power for the demanded speed. This converts the speed demand timeline to a power timeline. The diesel engine is modeled similarly, by converting the engine's performance chart into a two-dimensional LUT, taking engine speed and power as inputs, and returning the instantaneous specific fuel consumption (SFC). The cumulative fuel consumption is then the integral of the SFC values. The electric machine is modeled by its performance characteristic, with the power splitting and sharing being determined by a central control logic.

This steady-state modeling is valid since the quantities of interest (power flows and operating points) are required over a long period of time. Hence, transient response is not of particular interest for scenario fuel consumption determination. The batteries are modeled using Simulink's built-in battery model. This provides a model for Lithium-ion, Lead-acid and Nickel Metal Hydride batteries.

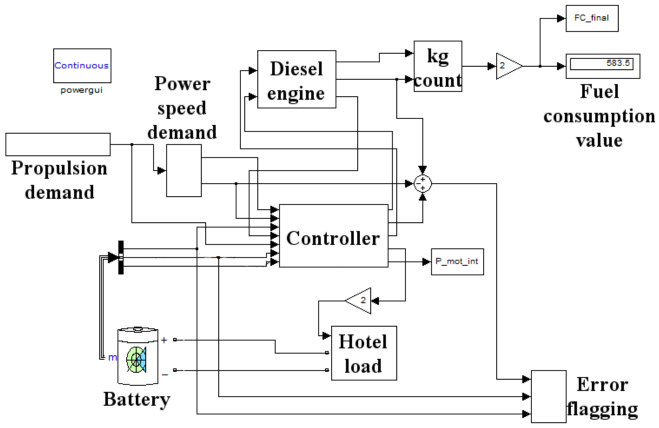

Figure 2. Complete Simulink model of parallel hybrid setup.

The central control logic controls the power demanded from the electrical machine and/or diesel engine, depending on the propulsion and hotel loadings, as well as the current operating point of the components. Critical above all is the batteries' state of charge, which is to be maintained within certain limits.

3 OPTIMIZATION

Hybrid vehicle design is generally approached from a satisfaction of specification. In a parallel automotive hybrid, an internal combustion engine (ICE) is sized to cater for the cruising speed demand, such that maximum speed on top gear is capable of being maintained. The low-speed side of the demand in turn influences the electric motor sizing. Together with the transmission system in use, this determines the acceleration capabilities of the vehicle. As a first-order design, the ICE can be assumed to cater for the steady-state rolling and air resistances, such that the electric drive is sized to completely meet the acceleration specification. The size of this motor can then be lowered by examining the power demanded for acceleration taking also into account the power provided by the ICE at low speeds (Ehsani et al. 2010).

For the ESS, the power requirement is selected to be greater than the motor's power rating to take into account conversion inefficiencies. The energy requirement is then dependent on the driving pattern to be catered for, and hence its regeneration potential. Taking into account the inefficiencies associated with the process and the desired initial and end capacities, then the stored energy requirement can be calculated. This design is then followed by simulation, when values such as fuel consumption can be calculated. Iterative design can then be performed in order to improve any aspect of the system (Ehsani et al. 2010).

Yet with such a design for satisfaction of specification, attributes such as fuel consumption, emissions and system weight are secondary values over which the designer has no direct control. Intuitive design, and experience help to direct the design and improve these parameters, however, the design does not address these parameters as an objective.

Optimization is a process whereby an objective is addressed directly and an extreme value (either maximum or minimum) located. This permits objectives to be aimed for and designed for, rather than following as a secondary consequence from design.

Classical optimization techniques would involve the use of mathematical tools such as the Newton-Raphson or steepest descent methods. These however require a mathematical equation for the problem description, something which can't be done to quantify the fuel consumption over a scenario. Furthermore, these methods all consider continuous and linear functions. When considering discrete component availability, classical optimization techniques fail for this problem.

Genetic algorithms take a cue from nature as the ultimate optimizer. Without requiring in depth knowledge of the problem at hand, genetic algorithms operate directly on a descriptor of the problem, treating the underlying function as a black box, requiring only the returned value. This robust approach based on simulation is therefore highly adept at optimizing hybrid vehicles, evidenced by works such as (Desai & Williamson 2009), (Jain et al. 2009) and (Hasanzadeh et al. 2005).

All the possible combinations of components making a hybrid setup represent the search space, from which the optimal configuration is chosen. In keeping with the genetic analogy, the descriptor for the component configuration is termed a *chromosome*. Corresponding to each chromosome in the *search space* is a *solution* in the *objective space*. This maps the chromosome to the objective value of interest such as fuel consumption.

The mapping from search to objective space is performed by the fitness function. Optimization is therefore performed on the solutions in the objective space, returning the fittest chromosome as the implementation to be selected.

Compared to classical methods, genetic algorithms are global routines, capable of locating population optima, rather than local ones. This is done without knowledge of any auxiliary parameters such as derivatives of the function, enabling genetic algorithms to be a robust method of global optimization.

Operating solely on the chromosome representation, the search for optima revolves around three operators. Considering a population of chromosomes, the *selection* operator identifies the fitter chromosomes to be used to generate the next generation. The next generation comes about by *reproduction*, whereby the previously selected chromosomes are used to form a new chromosome, termed the offspring. This represents the search through the search space and is responsible for locating the global optimum. Finally, the *mutation* operator provides an insurance against premature convergence by introducing a random variation to offspring to ensure that the search does not become stuck at a local optimum.

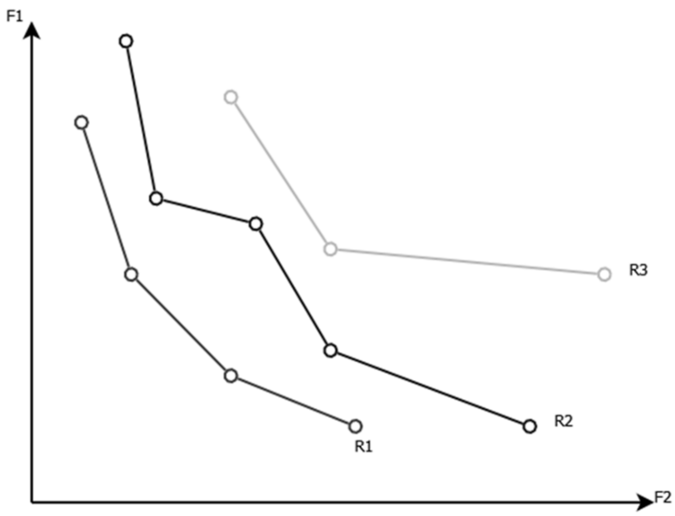

Figure 3. Three non-dominated ranks for bi-objective problem.

3.1 *Multi-objective optimization*

Despite the apparent straight-forwardness of optimization using genetic algorithms, optimization for a single objective does not reflect real-world practicalities. Locating an optimum with respect to a single objective would give an optimized solution, yet one which inherently ignores any other aspect of the problem. Referring to the problem of a hybrid motoryacht, optimizing for fuel consumption would result in a large battery capacity (to minimize engine operation and hence fuel consumption), yet come in at a large weight and cost.

Such a solution would be impractical from an application point of view, so a compromise must be found between locating an optimized solution from the consumption perspective, as well as the weight or installation point of view. Compromise should not imply substandard performance, but rather an addressing of differences.

A multi-objective optimization problem can trivially be converted to a single-objective one by means of a weighting vector, where multiple objectives are added up after being weighted to form a single metric. This however requires a priori knowledge of the demanded weighting. Results can therefore be biased since this decision is taken without any indication of results.

Basing the weighting after obtaining a set of results is possible by using the concept of non-domination and Pareto-ranking of solutions. Instead of delivering a single final solution, a set of optimized, compromise solutions is obtained, from which the final solution is chosen by the user using higher-level information. This higher-level information is experience-based and generally reflects non-technical influences, such as preference for particular components, or an inclination towards individual objectives. Though in effect this represents the use of a virtual weighting vector, the weighting values are applied to a set of results, thus the selection is based on actual solutions without postulating and introducing blind biases (Deb 2001).

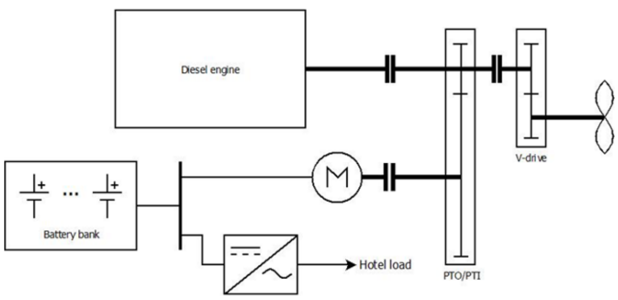

Figure 4. Proposed parallel hybrid implementation for hybrid motoryacht.

A very popular and efficient algorithm implementing a Pareto-based approach is the NSGA-II developed in (Deb 2002). The population is quickly sorted into ranks using the concept of non-domination, whereby a solution is said to be non-dominated with respect to another, if in going from one to the other, a certain sacrifice is demanded in one objective for a gain in the other, clearly illustrated as Figure 3. This shows a number of ranks, with R1 being the fittest rank. There is no benefit in choosing a solution from the lower ranks, but they can be used to search for new solutions, possibly giving better results.

Solutions in the first rank are the fittest, and this ranking value is used for selection purposes, as opposed to an explicit fitness value. This permits the comparison of solutions with multiple objectives. In order to further prioritize solutions for selection, a crowding metric is used to identify solutions lying in more isolated locations. This emphasizes a search in zones still unpopulated to enhance the global nature of the search.

4 IMPLEMENTATION

The model of the proposed parallel hybrid (Figure 4) was built in Simulink as outlined previously, with the genetic algorithm coded in Matlab.

The aim was to minimize both fuel consumption as well as installation weight, in order to determine the best compromise solution. The demand timelines are given as Figure 5 for both the propulsion as well as the hotel loads. The components to be optimized are the diesel engine, the electric motor/generator, the gearbox ratio and battery capacity as well as type. Optimization is also performed on the controller itself. This allows an even broader search space and permits the exploration of different control strategies.

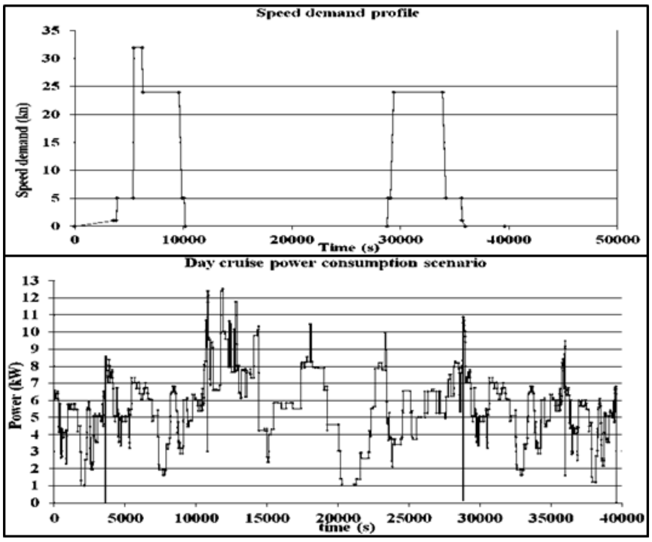

Figure 5. Propulsion (top) and hotel load demand timelines for sixty-foot motoryacht for day cruise scenario

4.1 *The controller*

The control strategy determines the points at which the vessel changes operating modes. For a parallel hybrid, four basic modes are identifiable, namely:

– Electric-only mode – all loads are supplied by the electric system from the batteries.
– Conventional mode – the diesel engines provide propulsion while the hotel load is supplied via inverter from the batteries.
– Assist mode – the electric motor connected to the batteries is used to assist the diesel engine during acceleration or high power demands, with their power added up at the gearbox.
– Charging mode – the diesel engine is run to provide propulsion and also supply the electric generator to recharge the batteries. Hotel load is supplied off the electric generator.

A speed and/or power level can be defined to control the changeover of modes, depending on the battery state of charge. Charging mode is enabled whenever the battery is discharged, while the other propulsion modes are only possible if the charge level is sufficient.

Operating the diesel engine at low power levels will result in high SFC values, in addition to suboptimal performance in terms of combustion, leading to higher wear and maintenance requirements. Thus, using electric propulsion for low demands is an obvious candidate for improving fuel consumption. However, raising the point to which electric propulsion is maintained necessitates increasing the battery size. Hence, the correct balance must be found. Likewise, the point at which assist mode is demanded can permit engine downsizing, but can lead to significantly longer charging times.

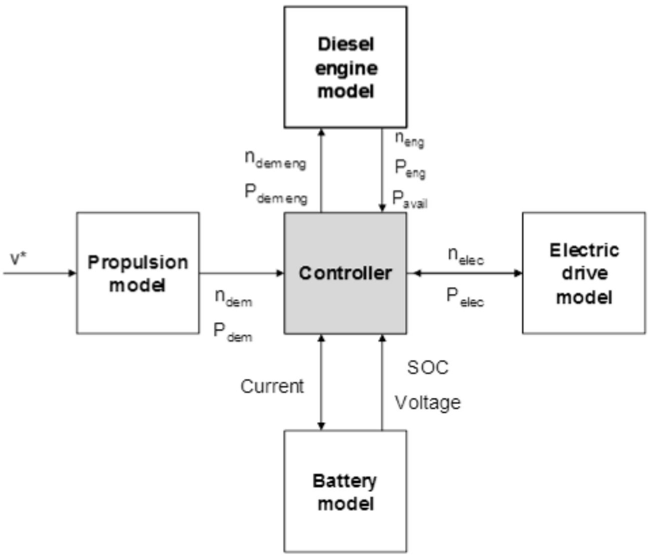

Figure 6. Power flows, with component set points decided by controller

The point at which assist is performed is a function of the diesel engine's loading, and hence the level of parallel operation demanded between motor and engine. Varying this level therefore allows the assist point to be optimized in order to determine the best load sharing. The changeover from electric-only to conventional mode is defined mainly by the electric motor's power and speed ratings, since electric operation is permitted only in this window.

Figure 6 illustrates the relation between the controller and the other simulated components. Based on the power demands and each components' current operating point, the controller outputs the desired setpoints for each component depending on its control strategy.

4.2 *Chromosome representation*

Based on these variables for optimization, the chromosome for searching through the search space was defined as consisting of the following elements:

– Diesel engine index
– Battery type
– Number of parallel batteries
– Electric motor rating
– Gearbox ratio
– Engine power sharing point
– Electric-only launch power

These all represent a particular hybrid setup from a database of components taken from manufacturer brochures. Thus every solution actually represents implementable setups. Real number representation is used, since this permits infinite database growth (without requiring chromosome modification as with binary coding) as well as avoiding Hamming cliffs which present an artificial hindrance to a gradual search (Deb 2001).

Using real numbers requires some modification to the standard algorithm, namely that a blending operator is used instead of explicit crossover. BLX-α was implemented with an α-parameter of 0.5 to give the best balance between exploration and exploitation (Herrera et al. 1998).

4.3 *Crowding-distance metric*

The aims of multi-objective optimization are to identify the fittest possible set of compromise solutions, as well as explore the search space for a broader scope to this set. Deb proposes a crowded distance metric which identifies the biggest rectangle which can be fitted around a solution in the objective space (Deb et al. 2002). Yet this was found to give unsatisfactory results in this implementation, with limited final solution diversity. This is explained as being due to solutions having different chromosome makeup, yet giving similar solution values, thus decreasing an objective space metric's effectiveness.

This was further noted by Desai in (Desai & Williamson 2009) for a similar application. Desai's approach in the search space involved calculation of the Euclidean distance for between each point. This however is quite computationally intensive. The authors propose a novel *uniqueness* counter which counts the number of repetitions for each element for each chromosome in a population. Figure 7 illustrates the functioning of this uniqueness counter on a sample population. This serves as an indicator as to how unique a solution actually is. Thus, during selection, in case of a tie between two solutions of equal rank, a more *unique* solution is preferred to ensure future diversity.

5 RESULTS

The algorithm was run for 100 generations in order to iterate towards the optimal rank of solutions. The equipment data was loaded from the component database, while the scenario hotel and propulsion timelines were obtained from previous work carried out within MI-SE@MALTA for a day cruise scenario for the 60-foot motoryacht under consideration (Grech 2009).

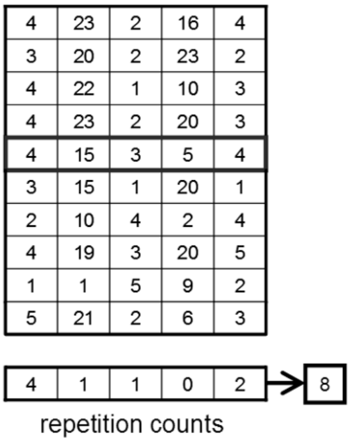

Figure 7. Uniqueness counter on sample population

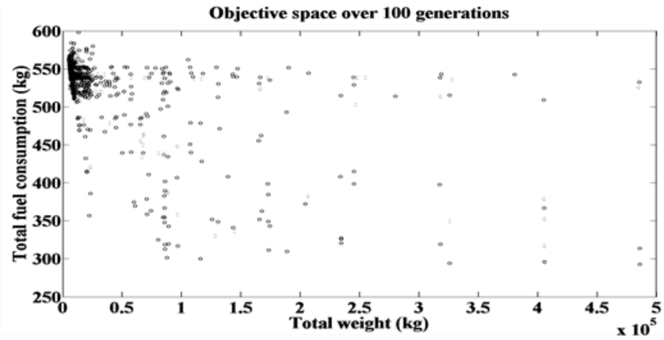

Figure 8. Solutions in objective space over 100 generations. Note convergence towards left hand side of space

A population of size 200 was used, together with a mutation constant equal to the reciprocal of the chromosome length (Deb 2001). This gives a mutation rate proportional to the number of variables involved. A constraint of 10 tons is also introduced. This serves to focus the search below a total weight of 10 tons, representing a realistic figure which would otherwise involve a significant performance loss due to the added installation weight. It must be noted that as a first order model, the demand power is considered to be independent of loading, though in actual fact increased loading would increase power demand and correspondingly the fuel consumption.

The progression of the genetic algorithm is seen in Figure 8, where starting off from a random distribution in the objective (solution) space, the solutions increase in fitness by gradually migrating towards the left hand side of the objective space.

Figure 9 illustrates the final rank of optimized solutions. These are all rank 1, expected since an overall fitness improvement is demanded. Infeasible solutions (greater than 10 tons) are not illustrated in this figure. It is from this plot that the final solution is chosen by the user, coupled with further information obtained from examination of the solution chromosomes themselves.

A sample of the solution chromosomes is listed in Table 1. These chromosomes correspond to the solutions observed in Figure 9 in the objective space. All solutions utilize the same diesel engine as the conventional system (895kW rated power). This is understandable since the top speed requirement is not reduced, which demands around 800kW of propulsion power. Though electrical assistance is possible, the energy capacity required from the batteries would be excessive, resulting in a very heavy solution, and hence these solutions are dominated and discounted in early generations.

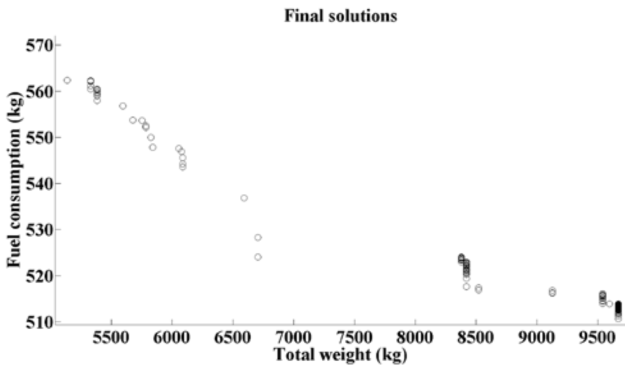

Figure 9. Final rank of optimized solutions

Also universally chosen was the option of having no gearbox connected to the electrical machine. Previous work (Sciberras & Norman 2010) without controller optimization had indicated a trend towards high speed machines coupled to a reduction gearbox.

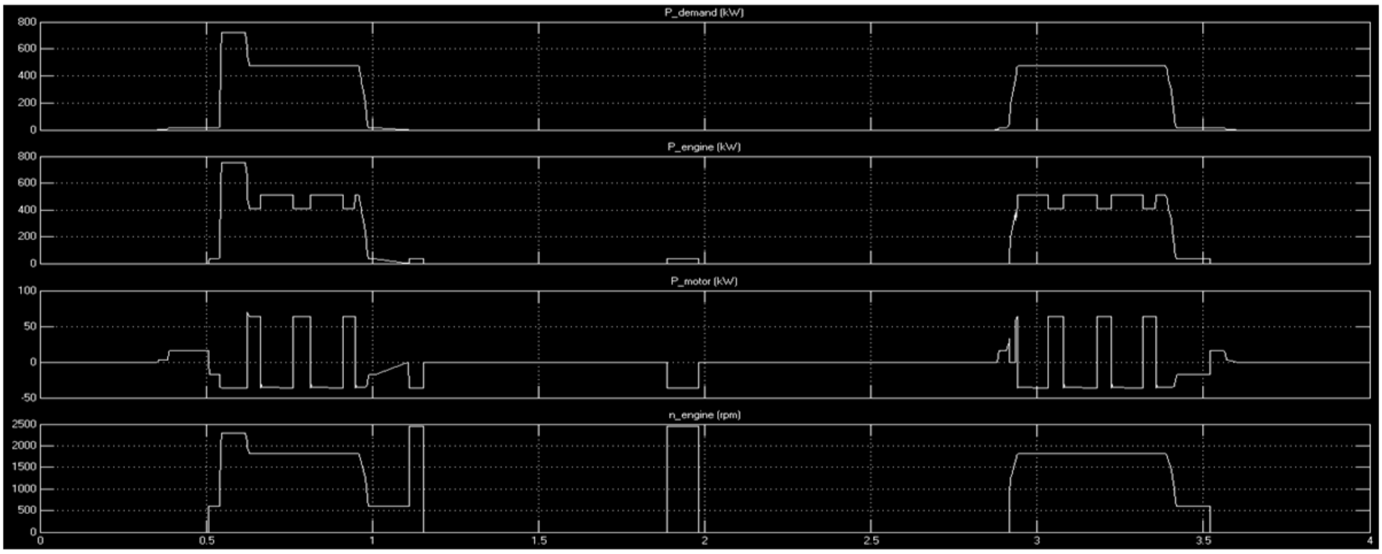

Figure 10. Component timelines for day cruise scenario. Chosen solution returns fuel consumption of 560.19 kg at a total weight of 5380kg.

Table 1. Selection of solution chromosomes after 100 generations. Repeated solutions have been omitted for clarity

Diesel engine rating	Motor rating	Motor speed rating	Total fuel consumption	Total weight	Battery capacity	Battery type	Diesel engine share point	Launch power
kW	kW	rpm	kg	kg	kWh		%	%
895	65	3000	562.40	5135.3	12.28	Li-ion	46	33
895	65	3000	562.40	5135.3	68.95	Li-ion	1	89
895	115	3000	562.20	5330.6	68.95	Li-ion	57	30
895	115	3000	562.22	5330.6	68.95	Li-ion	85	98
895	105	3000	558.99	5384.0	12.28	Li-ion	11	64
895	105	3000	560.19	5384.0	12.28	Li-ion	52	89
895	70	1800	553.70	5676.6	344.74	Li-ion	30	81
895	100	1800	553.69	5751.3	49.10	Li-ion	41	80
895	260	3000	552.51	5784.0	12.28	Li-ion	44	77
895	260	3000	552.12	5784.0	34.47	Li-ion	38	42
895	150	1800	549.97	5826.0	36.83	Li-ion	33	79
895	220	3000	547.86	5841.3	49.10	Li-ion	30	100
895	150	1800	547.55	6056.6	344.74	Li-ion	33	57
895	175	1800	546.92	6076.6	24.55	Li-ion	44	66
895	175	1800	546.92	6076.6	68.95	Li-ion	43	44
895	150	2400	523.55	8380.0	344.74	Li-ion	98	76
895	240	3600	521.52	8420.0	344.74	Li-ion	61	78
895	240	3600	522.88	8420.0	344.74	Li-ion	78	51
895	220	3000	520.31	8420.0	344.74	Li-ion	77	81
895	290	3600	516.94	8520.0	344.74	Li-ion	50	59
895	190	2400	517.44	8520.0	344.74	Li-ion	40	92
895	260	3000	516.86	9128.0	413.68	Li-ion	57	55
895	260	3000	516.32	9128.0	413.68	Li-ion	91	82
895	230	2400	516.09	9540.0	413.68	Li-ion	87	65
895	230	2400	515.99	9540.0	413.68	Li-ion	75	69
895	230	2400	514.00	9540.0	413.68	Li-ion	54	95
895	230	2400	514.56	9540.0	413.68	Li-ion	68	91
895	290	3000	513.92	9598.0	413.68	Li-ion	82	76
895	390	3600	512.62	9668.0	413.68	Li-ion	55	48

The controller optimization however now allows the motor's operating point to be variable and hence the additional weight of a gearbox can be avoided by locating a different launching power value.

The results clearly indicated the trend towards an energy dense solution. This involved Lithium-ion batteries and permanent magnet machines. Lithium-ion batteries offer the best specific energy capacity, essential for a marine hybrid where energy recuperation is largely absent. Though these involve significant cost compared to traditional lead batteries, their performance is highly superior (Lukic et al. 2008).

Likewise, permanent magnet machines offer greater power densities compared to conventional machines. This is due to the field excitation being provided by permanent magnets, removing the need for external excitation, and therefore greater efficiencies. This in turn implies a greater proportion of stored energy being converted to usable power. Permanent magnet machines are therefore more compact and lighter compared to their conventional cousins and are nowadays available off the shelf from several manufacturers. Permanent magnet machines also provide for more efficient generation capability.

The final setup choice is made by the user based on Figure 9 (visualizing the objective space) and Table 1 (illustrating the search space). Engineering experience and intuition now come into play, as well as reflecting preferences towards objectives. Aiding in the decision making, the user can visualize and examine the power flows for the selected solutions, such as Figure 10, by simulating a particular solution's behavior.

6 CONCLUSIONS

Objective design by simulation permits optimization of hybrid vehicles such that attributes such as fuel consumption can be aimed for and achieved by correct design. Classical optimization techniques are not able to successfully operate on complex models such as hybrid vehicles, hence genetic algorithms present a very powerful and robust way of arriving at optima by mimicking natural evolution.

A model was developed to calculate the fuel consumption of a hybrid motoryacht based on steady-state parameters. In turn, an optimization algorithm was developed to choose the best hybrid components as well as optimal controller values. This allows a hybrid vehicle to be virtually 'bred' from a computer.

Optimization is essential in marine hybrids, since the absence of regeneration implies that any savings must come about by improved component operating points. Intuitive design satisfies performance requirements, but does not guarantee fuel savings. This is emphasized by design by simulation, coupled with a robust optimization routine.

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