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Automated design and optimization of industrial motion control machines: verification and a case-study

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Abstract. Motion control is a form of automation which enables the position- or velocity-control of a machine using an actuator such as an electric motor. The selection of suitable components and actuators for complex mechanical structures requires significant engineering expertise and intelligence. In this work, a design expert system is presented to support the motion control system design process through optimization of mechanical components and accurate selection of an actuator-transmission combination for the system. Verification of the developed system is conducted on an industrial conveyor belt. A case study involving a heavy-weight industrial hoister driven by a DC motor is presented, where the developed automated system is found to consistently outpace human performance on the same design tasks.

1. Introduction

The automation of engineering design and product development is of great significance in competitive industries. An automated system improving existing engineering design should include fault detection, modelling, and optimization capabilities, along with some form of intelligence equivalent to humans. In this paper, a Design Expert System (DES) is developed to act as the human design expertise segment of an automated engineering design system. The overall system within which the DES works is the Evolutionary Design Framework (EDF) shown in figure 1, previously devised by de Silva [1].

The EDF contains three main sub-systems: a Machine Health Monitoring System (MHMS), a Modeling and Evolutionary Design Optimization System (MEDOS), and a Design Expert System (DES). All these sub-systems work together to perform automated design evolution [2]. In the EDF, the MEDOS is primarily responsible for the development of new design proposals, fulfilling given constraints such as a target response. The main search mechanism used by the MEDOS is Genetic Programming (GP), developed by Koza [3, 4]. GP is often integrated with modelling techniques such as Bond Graphs (BG) or Linear Graphs (LG) to expand the design space into multiple domains. Seo et al. [5] were the first to propose a GP-BG integration, and other works followed suit [6, 7]. The modeling stage of the MEDOS is an important prerequisite to efficient optimization

In the context of the EDF, the DES is essential in that it provides a much needed intelligent human judgment element to the overall process. The DES harbors domain-specific human expertise in design and general common sense judgment in a system which can operate at a much lower cost and higher speed than a human expert. It supervises and guides the evolution and optimization of improved designs, then assesses the practical feasibility of the proposed design improvements. The domain of



the DES in this work is motion control design and drive selection. The authors believe the capabilities of the DES presented in this paper are unique in its domain, especially its ability to initiate and guide iterative optimization routines. Previously, researchers have developed expert systems in this same domain that, for instance, aid in the simulation and controller tuning of an AC drive system [8] or automate the selection of drive structures [9], AC drives [10], inverter-motors [11], or machining devices [12]. However, development of expert systems which are not stand-alone, or can be integrated in bigger fault diagnosis, design/redesign, and optimization schemes is lacking or non-existent.

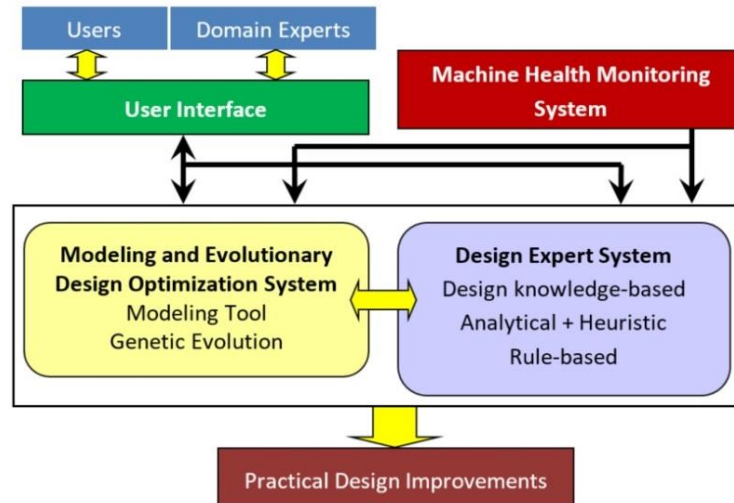


Figure 1. Flowchart of Evolutionary Design Framework.

In this paper, a DES which is synchronized with an external gradient-based optimization routine is developed and tested. The DES supplies the optimization routine with domain-specific human knowledge on constraints, data, and practical design parameter ranges to improve the optimization results. The effect this guidance has on the overall proposed design alternative is measured and reported through a practical case-study of an industrial hoister.

2. System implementation and verification

Implementation of the DES is performed in Microsoft® Visual C++. The core code of the DES is written as a large list of sequential if-then type clauses, or rules. Based on inputs to the DES Graphical User Interface (GUI), the routine enters through the applicable rules in their appropriate order.

Table 1. Sample specifications for motors used in MCDES.

Motor #	J_m	ω_{nom}	T_{nom}	η
353295	1.29×10^{-4}	3640	0.51	0.84
353296	1.38×10^{-4}	3550	0.65	0.87
353297	1.34×10^{-4}	3270	0.75	0.89
353300	1.28×10^{-4}	2820	0.83	0.89

The MCDES motor and gear database is built from over 50 different motors and compatible gears from Maxon® Motor Corp. The polar moment of inertia of the motor (J_m) and the gear (J_g), in addition to the gear ratio (p) values for each motor and gear are included in this database. Other parameters such as motor torque capabilities (T_{nom} and T_{max}), speed (ω_{nom} and ω_{max}), and maximum efficiency (η) are also included. The MCDES is synchronized with easily updatable external Excel® spreadsheets containing all the motor and gear information to accommodate future updates and modifications. The required motor and gear specifications, for example those in tables 1 and 2, respectively, are taken directly from these spreadsheets in a seamless fashion.

Table 2. Sample specifications for gears used in MCDES.

Gear #	J_g	p	Gear group	η
110408	1.65×10^{-5}	3.7	6	0.80
110409	1.55×10^{-5}	14	6	0.75
110410	1.25×10^{-5}	25	6	0.75

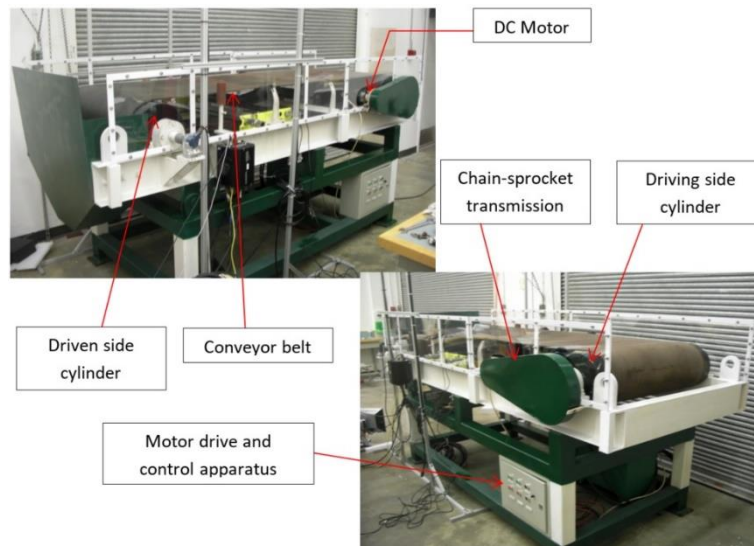
2.1. GUI in Excel[®]

The MCDES code interprets the type of motion control design (generic or custom) and reads the required properties directly from a GUI in Excel[®]. Ultimately, this feature allows for easier integration of the MCDES with the MEDOS of the same domain, as discussed previously. The Excel[®] GUI also allows for advanced processing of the design data, such as optimization of custom components like shafts and transmissions. The template is synchronized with an optimization routine in Matlab[®] which reads the proposed design values, optimizes them based on imbedded expertise, and then overwrites the proposed values with the optimized values. This is demonstrated in the case study below.

2.2. Verification results

Verification of the MCDES selections was performed using pre-evaluated test scenarios for each generic application. During all verification procedures, there were evident differences between using the MCDES and the manual selection of the motor or motor gear drive:

- The MCDES takes a fraction of the time (especially for custom structures and duty cycles, or motor drives with gearhead)
- Time-intensive and difficult calculations (such as in profiling smooth response curves) are not short-cut or discarded altogether
- The MCDES does not mistakenly miss selections or lose competence during extended runs

**Figure 2.** Conveyor belt setup used for verification of DES.

The developed MCDES was also tested through selection of a drive for an existing industrial setup – this was chosen to be a conveyor belt used for transporting mining aggregate pictured in figure 2. All pictures and design data mentioned herein are courtesy of Motion Metric International Corporation. Geometric dimensions, mass parameters, and load profiles used for this test are listed in table 3. The specifications of the motor that were selected by the MCDES were compared to the motor being used in the existing setup, which had a T_{nom} of 2.9 Nm and a ω_{max} of 2500 rpm. Parameters were chosen to simulate the largest torque requirement for the motor corresponding to the maximum linear system speed specified by the manufacturer (i.e. 65 feet per minute). With these design parameters, the

MCDES selected a motor within a 10% range of the actual motor for the setup (Torque required and ω_{max} were 3.18 Nm and 1044 rpm, respectively). This verification confirms accurate functionality of the MCDES program within reasonable limits of existing industrial designs.

Table 3. Design data for DES verification on conveyor belt setup.

Parameter	Value
Maximum load mass	30 kg
Belt width, thickness, and mass	0.762 m, 0.008 m, 5.7 kg
Conveyor length (between cylinder centers)	2.33 m
Cylinder diameter (driving = driven)	0.3048 m (1 foot)
Cylinder mass	10 kg
Large sprocket diameter, mass	0.3 m, 4.54 kg
Small sprocket diameter, mass	0.06, 0.075, or 0.09 m (use largest), 0.5 kg
Chain weight	~ 1 kg
Chain sprocket drive efficiency	95%

3. Automated design optimization

The MCDES design optimization feature mimics an optimal design scheme in the motion control domain. In optimal design, a designer's experience can be used to tackle global, conceptual design issues, while the detailed design analysis can be performed using specialized numerical methods. Using its practical domain-specific expert knowledge, the MCDES guides the external design optimization in more feasible directions of search and optimization. The external optimization routine used is Sequential Quadratic Programming (SQP). SQP methods are a class of gradient-based methods of optimization which offer a superior rate of convergence over other methods [13].

3.1. Hoister case-study

One of the generic applications in the MCDES is a vertical hoisting mechanism application, which can be attached to the motor rotor directly. For this case study, the high-level custom mechanical structure shown in figure 3 is built in the MCDES. Instead of just a generic hoister, a hollow shaft simply supported by two bearing housings is placed between the driven pulley wheel and the rope winch, to reach loads farther away from the belt-pulley plane. The role of the external optimization routine in this case study is to minimize the weight, complexity, and consequently, the cost of this modification component without sacrificing the structural or functional integrity of the system.

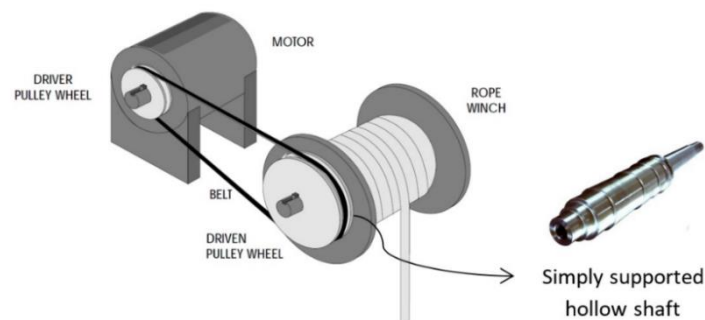


Figure 3. High-level custom hoister design with added component.

The optimization routine has built-in expertise of the numerical constraint limitations for each component according to various design scenarios. For each component that can be optimized, it also contains the objective function, relevant constraints (such as stress, buckling, deflection, etc.) and the practical ranges for each design variable. For example, it is impractical for the outer diameter of a hollow shaft to be smaller than 1 cm, or larger than 15 cm.

3.2. Problem formulation

The formulation of the important equations coded into the optimization routine is demonstrated here for the hollow shaft component. The shaft is under constant torque a function of the radius of the winch pulley and the weight of the hoisted load. The shaft transmits the torque and also carries its weight, simplifying the problem into a hollow shaft cantilever under torsion. If the shaft weight is neglected, torsion will be the only load the shaft experiences. The objective function is shown in Equation 1 below. The three constraints limiting the reduction of the size of design variables (d_o and d_i) beyond structural limits are shown in Equations 2a – 2c. To avoid getting a thin-walled shaft as the optimal solution, a constraint is placed on how close the inner diameter of the shaft can be to the outer diameter (Equations 3a – 3c). For larger shafts, the weight of the shaft itself cannot be neglected. A constraint for the combined loading effect is added to account for this.

$$\text{Minimize } f = \frac{\pi}{4} (d_o^4 - d_i^4) L \rho g \quad (1)$$

$$\text{Stress: } \tau_{max} = \frac{T r_o}{J} \quad \text{or} \quad \frac{T \left(\frac{d_o}{2} \right)}{\pi \left(\frac{d_o^4 - d_i^4}{32} \right)} - \tau_{allow} \leq 0 \quad (2a)$$

$$\text{Twist: } \theta = \frac{T}{GJ} L \quad \text{or} \quad \frac{32 \cdot T \cdot L}{G \cdot \pi (d_o^4 - d_i^4)} - \theta_{allow} \leq 0 \quad (2b)$$

$$\text{Buckling: } T \leq (T_{cr})_{buckling} \quad \text{or} \quad T - \frac{\pi d_o^2 E}{12 \sqrt{2} (1 - \nu^2)^{0.75}} \left(1 - \frac{d_i}{d_o} \right)^{2.5} \leq 0 \quad (2c)$$

$$1 \text{ cm} = d_{i \min} \leq d_i \leq d_{i \max} = 6 \text{ cm} \quad (3a)$$

$$2 \text{ cm} = d_{o \min} \leq d_o \leq d_{o \max} = 7 \text{ cm} \quad (3b)$$

$$d_i \leq 0.9 d_o \quad (3c)$$

The shaft is still simply supported on bearing housings, so the vertical force from the hoisted load is supported by the nearest bearing and is not felt by the shaft, assuming the nearest bearing is sufficiently close to the hoisted load application point so that it carries the majority of the load. The added uniform distributed load along the length of the shaft, representing the weight of the shaft, creates a transverse shear and a moment in the shaft as a function of position x , as shown in Equations 4a and 4b. Assuming a uniform cross-sectional area, the maximum moment occurs at half-length and is given by Equation 5a. The maximum normal stress in the shaft due to bending moment and the maximum shear stress due to torque are shown in Equations 5b and 5c. To find the stress constraint, the principal stress for this 2D stress state is found (Equation 6) and the Tresca failure criterion is applied. The constraint is a nonlinear inequality (Equation 7) as a function of the design variables. Finally, the limits on the design variables and the dimension relation constraint are the same as in Equations 3a – 3c.

$$V = \frac{F_{weight}}{L} (L - x) \quad (4a)$$

$$M = \frac{\frac{F_{weight}}{L} x}{2} (L - x) \quad (4b)$$

$$M = \frac{F_{weight} \cdot L}{8} \quad (5a)$$

$$\sigma = \frac{32 M D_o}{\pi (D_o^4 - D_i^4)} \quad (5b)$$

$$\tau = \frac{16 T D_o}{\pi (D_o^4 - D_i^4)} \quad (5c)$$

$$\sigma_{PP} = \frac{\sigma}{2} \pm \sqrt{\left(\frac{\sigma}{2} \right)^2 + \tau^2} = \frac{16 M D_o}{\pi (D_o^4 - D_i^4)} \pm \frac{1}{2} \left[\left(\frac{32 M D_o}{\pi (D_o^4 - D_i^4)} \right)^2 + 4 \left(\frac{16 T D_o}{\pi (D_o^4 - D_i^4)} \right)^2 \right]^{\frac{1}{2}} \quad (6)$$

$$\text{Tresca: } \sigma_{11} - \sigma_{33} \leq \sigma_{allow} \quad \therefore$$

$$\left[\left(\frac{32MD_o}{\pi(D_o^4 - D_i^4)} \right)^2 + 4 \left(\frac{16TD_o}{\pi(D_o^4 - D_i^4)} \right)^2 \right]^{\frac{1}{2}} - \sigma_{allow} \leq 0 \quad (7)$$

3.3. Case study results

To initiate the optimization process, a starting point for the design variables must be identified. This starting point is not the optimized value and may be infeasible when using SQP optimization. Hence, the values are taken from the MCDES. Table 4 shows the results obtained from running simulations with varied design specifications (such as material choice) from the MCDES. Motor selection is performed using the optimized values and compared to motors selected for the starting point values. It should be noted that the stopping criteria only ensures that a local minimum is reached, thus, depending on the starting point, the final solution might or might not correspond to the global minimum. Nevertheless, an improvement will most often be made on the starting point within the aforementioned design constraints. These results are fed into the MCDES for motor selection. The impact the component optimization has on the motor torque requirements is evident in the right-most column of table 4. This change in motor torque reflects the increase or reduction of the size and cost of a motor. In simulations with only two design variables, like the hollow shaft component, the results can also be expressed graphically. Figure 4 is an example of this, where weight contours (objective function) for two different materials are plotted with constraints overlaid on the plot area. The blue rectangular border represents the range of the design variables. A feasible solution is any point on a contour above all the constraints yet within the blue rectangle.

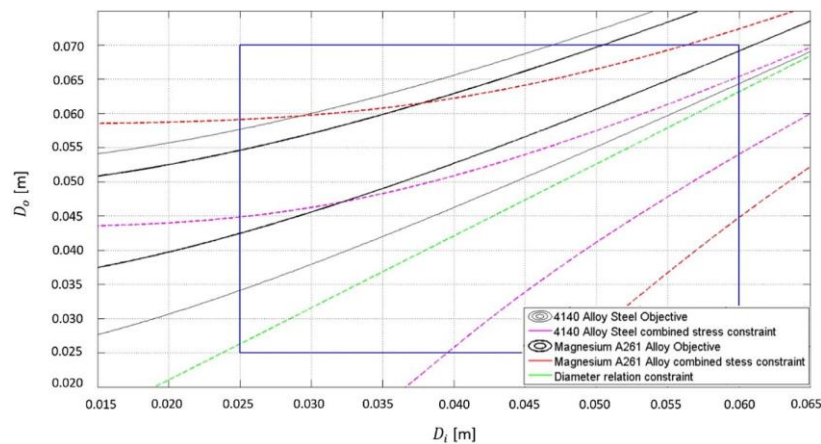


Figure 4. Graphical comparison of 4140 Alloy Steel and Magnesium A261 Alloy in optimization with shaft weight considered.

Table 4. Optimum solutions vs. shaft material & impact on T_{motor} (shaft weight considered).

Starting Point [d_{i1}, d_{o1}]	Material	Optimum Solution [d_{i*}, d_{o*}]	T_{motor} change (all else constant)
[0.06, 0.07]	4140 Alloy Steel	[0.035, 0.047]	-13.4%
[0.06, 0.07]	Aluminum Alloy 24 ST4	[0.05, 0.067]	+1.96%
[0.06, 0.07]	Magnesium Alloy A261	[0.058, 0.077]	+5.69%
[0.06, 0.07]	Beryllium	[0.047, 0.063]	~ 0%
[0.06, 0.07]	Titanium	[0.045, 0.061]	-2.98%

In table 5, the shaft material is kept the same (4140 Alloy Steel) and the core design parameters are increased at varied rates. Also, the starting point values are increased at a steady rate following the same trend as the design parameters. Then, the optimal solution for each case is simulated and compared to the starting point values. The difference between the starting points determined by human judgment and the optimized points from simulation is more than 50%. The effect of this reduction in

size on T_{motor} is evident through MCDES integration, displaying the significant reductions in cost and size the intelligent expert system developed in this paper provides.

Table 5. Optimum solutions vs. human judgment and impact on T_{motor} (shaft weight neglected).

Starting Point [d_{i1} , d_{o1}]	Core design parameters [L , M , R]	Optimal Solution [d_{i*} , d_{o*}]	T_{motor} change (all else constant)
[0.05, 0.08]	[0.1, 500, 0.05]	[0.02, 0.027]	-11.9%
[0.06, 0.09]	[0.15, 750, 0.1]	[0.025, 0.033]	-4.86%
[0.07, 0.1]	[0.175, 980, 0.105]	[0.028, 0.037]	-5.63%
[0.08, 0.11]	[0.18, 1500, 0.145]	[0.044, 0.058]	-2.68%
[0.09, 0.12]	[0.3, 2500, 0.16]	[0.046, 0.061]	-2.96%

4. Conclusions

A Design Expert System which is able to guide the evolution of optimal design alternatives and accurately select motors for motion control systems has been presented in this work. Principles and procedures of motion control design and motor selection were used to create a comprehensive knowledge base for the design expert system. A systematic motor selection methodology which can incorporate generic or custom mechanical structures together with generic or custom duty cycles of the load was proposed and incorporated into the developed system. Results from the developed system were verified against human designer results and the specifications of an existing industrial setup. The design expert system offered significant benefits in efficiency and completeness. This work also presents a novel method of using computer-based artificial intelligence instead of human experts to guide and set-up iterative optimization processes and assess the practicality and real-world practicality of the results. This greatly facilitates the development of fully autonomous engineering design and redesign methods, where existing engineering systems can autonomously be monitored for faults or design weaknesses, diagnosed, and redesigned into feasible alternatives.

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References

- [1] Government of Canada IC 2012 Canada Research Chairs. <http://www.chairs-chaire.gc.ca/chairholders-titulaires/profile-eng.aspx?profileID=2529>
- [2] Gamage, LB, de Silva CW and Campos R 2012 *Mechatronics* **22** 83
- [3] Koza JR 1994 *Stat. Comput.* **4** 87
- [4] Koza JR 1994 *Genetic Programming II: Automatic Discovery of Reusable Programs*. MIT Press, MA, USA
- [5] Seo K, Fan Z, Hu J, Goodman ED and Rosenberg RC 2003 *Mechatronics* **13** 851
- [6] Razavi B and de Silva CW 2010 *Int. J. Inf. Acquis.* **7** 177
- [7] Samarakoon BL, Gamage LB and de Silva CW 2016 *Mechatronics* **33** 71
- [8] Chhaya SM and Bose BK 1995 *Proceedings of the 1995 IEEE IECON* **1** 712
- [9] Gerbaud L, Bignon J and Champenois G 1993 *Proceedings of the 1993 IEEE IECON* **1** 360
- [10] Chen D and Bose BK 1992 *Proceedings of the 1992 IEEE Industry Applications Society Annual Meeting* **1** 387
- [11] Fezzani D, Piquet H and Foch H 1998 *J. Appl. Phys.* **4** 53
- [12] Rubio L, De la Sen M, Longstaff AP and Fletcher S 2013 *Expert Syst. Appl.* **40** 2312
- [13] Belegundu AD and Chandrupatla PTR 2011 *Optimization Concepts and Applications in Engineering* Cambridge University Press, New York, USA