

Investigation of Tradeoffs between Efficiency, Mass, Cost, Service Factor, and Power Factor in Induction Machines

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ABSTRACT

The focus of this research is to perform a detailed investigation of the tradeoffs between mass, efficiency, service factor (SF), power factor (PF), and cost of commercially available induction machines (IMs). To support this effort, data from a large number of IMs is used to establish Pareto-optimal fronts between these competing objectives. From the Pareto-optimal fronts, relatively straightforward models are formulated for the mass versus loss, cost versus loss, SF versus mass, PF versus cost. Parameters of the models are obtained using a genetic algorithm (GA).

Keywords

Cost, efficiency, induction machines, loss, mass, Pareto-optimal front, performance tradeoffs, power factor, service factor

INTRODUCTION

The purpose of the research presented herein is to perform a detailed investigation of the tradeoffs between mass, efficiency, cost, SF, and PF of commercially available induction machines. To support this effort, data from 16,784 IMs was used to establish Pareto-optimal fronts between efficiency and mass, efficiency and cost, SF and mass, and PF and cost [1]. The machines included are from 18 major manufacturers and have rated speeds between 1200 rpm and 3600 rpm, rated powers between 1 HP and 500 HP, rated voltages between 200 V and 6600 V, masses between 13 kg and 3810 kg, and full load efficiencies between 50.5% and

96.5%. From the Pareto-optimal fronts, relatively straightforward models are formulated for the mass versus loss, cost versus loss, SF versus mass, and PF versus cost of IMs. It is important to note that since mass, cost, loss, SF, and PF are inherently dependent, a possible approach is to construct multi-dimensional Pareto-optimal fronts including all these objectives. Nevertheless, since it is difficult to conceptualize a Pareto-optimal front with more than three objectives, the studies in this paper include only two competing objectives (i.e. 2-D Pareto-optimal fronts). This research extends initial research into tradeoff modeling presented in [2]. Therein load conditions lower than full rated load are not considered. In addition, tradeoffs such as SF versus mass and PF versus cost are not provided.

The resulting models serve a number of purposes to the industrial and scientific communities. First, they serve as a measure of the state of the practice of existing machine design. Specifically, many researchers have proposed methods and algorithms for designing induction machines [3], [4], [5]. In the majority of the efforts, the results are shown for a single or low number of designs which limits the ability to consider design tradeoffs. In research that has structured machine design as a multi-objective optimization (i.e. minimize loss and minimize mass) [6], the focus has been domain specific; i.e. electromagnetic design without structural or thermal fields considered. Thus, the impact that thermal or mechanical considerations have on the performance is not clear. Since the models formed herein are based upon commercially available machines, these thermal and mechanical influences are inherently represented.

The second purpose is that the models can be used by engineers to quantify the impact that efficiency has on both the mass and cost of a machine. Knowledge of the expected mass for a specified efficiency and power level is useful in establishing reasonable performance specifications for electric machines used in various applications such as aircraft, spacecraft, and tactical vehicles. Knowledge of cost can be used to assess the short- and long-term economics of specifying a level of efficiency. In addition, if an IM is presumed to have an average load below the rated full load, one can examine the impact that machine over-sizing has on efficiency, cost, and PF in a given application.

Finally, tradeoffs between mass and SF allows one to investigate the impact of minimizing mass while maximizing SF. This enables one to evaluate the tradeoffs between mass and thermal overload constraints for applications where IM may experience recurring starts and stops, sudden changes in loading, operation with electric motor drive, or where fault ride through capabilities are of importance [7].

The paper is organized as follows. Section II briefly reviews the concept of the Pareto-optimal front and multi-objective optimization. In Section III the manipulation of the machines' information in the database is set forth to produce a metric where all machines are compared and non-dominated points are identified. Section IV describes the procedure of obtaining the closed-form expressions that represent the Pareto-optimal fronts for all the studies presented in the later sections. In addition, the section includes case studies of finding the Pareto-optimal fronts of loss versus mass and loss versus cost. Section V includes a brief discussion on SF in IMs, and a multi-objective optimization of mass versus SF is presented. Section VI includes a case study of the tradeoffs between PF and the initial cost of IMs in relation to their pole count and load conditions. Finally, the work herein is briefly summarized in Section VII.

PARETO-OPTIMAL FRONT

The theory behind multi-objective optimization is inherently different than single-objective optimization. In the case of single-objective optimization, the intent is to establish a global optimal solution [8]. However, in the case of multi-objective optimization there exist multiple and opposing objective functions. Each of the functions is to be minimized or maximized. Therefore, multi-object optimization results in a set of optimal solutions that describe the best tradeoff between conflicting objectives rather than a single, global solution [9].

In the case of single-objective optimization, the 'goodness' of a solution can be evaluated simply by determining its objective function value and comparing it to the values of other solutions. In multi-objective optimization, the goodness of a solution is evaluated using the concept of dominance. To

illustrate, it is convenient to suppose there are only two solutions X_1 and X_2 . The solution X_1 is said to dominate X_2 if the following two conditions are satisfied: (i) the solution X_1 is no worse than X_2 in all objectives, (ii) the solution X_1 is strictly better than X_2 in at least one objective.

As an illustration of the concept of dominance, consider a two-objective optimization problem with f_1 and f_2 . A goal is to maximize f_1 and minimize f_2 . Assume there are five solutions as in Fig. 1.

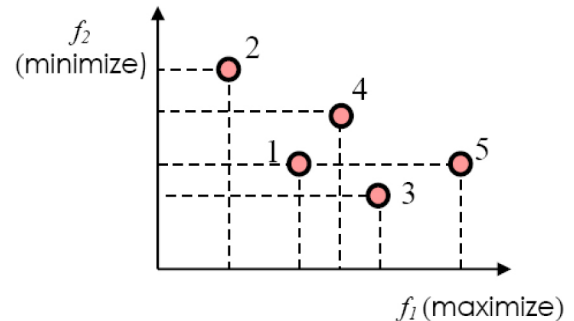


Fig. 1. Illustration of dominance in a 2-objective Pareto-optimization problem.

Comparing solutions 1 and 2, solution 1 dominates solution 2 for both objectives. Comparing solutions 1 and 5, both have the same f_1 value, but solution 5 has a larger f_2 value than solution 1. Thus solution 5 dominates solution 1. As a final example, consider solutions 1 and 4. Solution 4 is better for the first objective function, but solution 1 is better for the second objective function. As neither solution satisfies the first condition for the dominance test, we cannot say that either solution dominates the other. By testing each solution for dominance, the non-dominated solutions are given by points 3 and 5.

Given a set of solutions, the non-dominated solution set is a set of all the solutions that are not dominated by any members of the solution set. Each solution in the feasible decision space can be mapped to the feasible objective space. The non-dominated set of the entire feasible search space is generally referred to as the Pareto-optimal solution set. The boundary defined by the set of all points mapped from the Pareto-optimal solution set is called the Pareto-optimal front as shown in Fig. 2 [10].

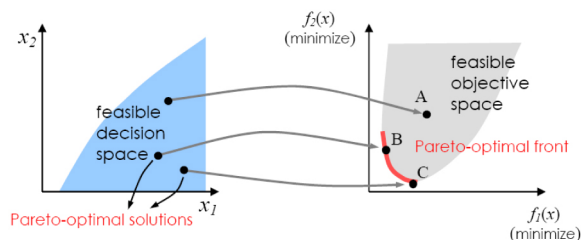


Fig. 2. Illustration of the mapping of solutions from the feasible decision space onto the feasible objective space.

MACHINE DATA

To model Pareto-optimal fronts for IM designs, it is necessary to have data from a wide variety of machines. The database used in this work includes a total of 16,784 machines; 3985 machines have a rated speed of 1200 rpm, 7786 have a rated speed of 1800 rpm, and 5014 have a rated speeds of 3600 rpm; corresponding to 6, 4, and 2 poles, respectively. The machines have rated powers between 1 HP and 500 HP, rated voltages between 200 V and 6600 V, masses between 13 Kg and 3810 Kg, and full load efficiencies between 50.5% and 96.5%. It is noted that since the number of IMs in the database with a rated speed of 900 rpm was relatively small, these IMs were not included in the modeling effort.

For proper comparison between the machines, the investigated IMs are ones with similar enclosures/cooling methods. These include Open Drip Proof (ODP) which is a relatively inexpensive enclosure where the vents are designed in such a way that water dripping on the motor will not normally flow into the motor. The motors are cooled by means of a fan directly coupled to the rotor. Also included was Totally Enclosed Fan Cooled (TEFC), which is likely the most commonly used motor enclosure in industry. In these machines, the motor is constructed with a small external fan on the rear shaft of the motor, usually covered by housing. The external fan is directly coupled to the shaft and blows air over the motor fins to remove excess heat. A final structure included is the Totally Enclosed Blower Cooled (TEBC), which uses a constant speed blower pulls air over the motor fins to keep the motor cool at all operating speeds [11]. A 3-dimensional plot of the machines in the database is shown in [Fig. 3](#).

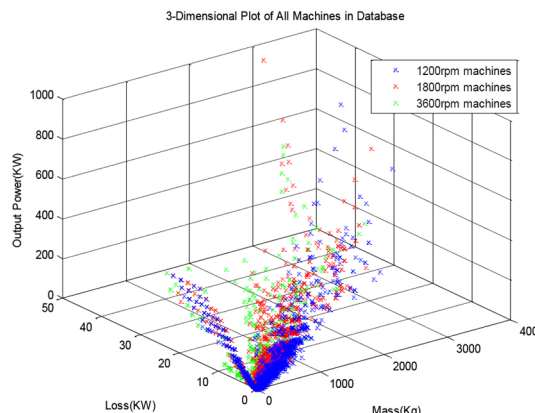


Fig. 3. 3D Scatter plot of machines in the database relating Mass, Loss, and Output Power.

Due to the large variance between machines' ratings, it is necessary to scale the parameters so that all machines, regardless of ratings, could be compared simultaneously. For this purpose, a number of new parameters are defined. These include the specific mass defined as

$$m_{spec} = \frac{m}{P_{out}} \quad (1)$$

where m_{spec} is the specific mass, m is the total mass of the machine, and P_{out} is the rated output power. the specific loss is defined as

$$P_{sloss} = \frac{P_{loss}}{P_{out}} \quad (2)$$

where P_{sloss} is the specific loss, P_{loss} is the total loss at, and p_{out} is the output power under rated conditions.

The machines are then divided into three speed categories: 1200 rpm, 1800 rpm, and 3600 rpm and the non-dominated points of specific loss versus specific mass are found. In addition, each speed category was further partitioned to three discrete load conditions; full load, 75% load, and 50% load. A plot of specific loss versus specific mass for 3600 rpm IMs at full load including identified non-dominated points is shown in [Fig. 4](#).

After inspecting the non-dominated machines in all three speed categories, two important observations are noted. First, almost all of the enclosure types of the machines on the Pareto-optimal fronts are either TEFC or ODP. These two enclosures are almost equally distributed and there does not seem to be an advantage of one enclosure over the other from an efficiency perspective. Second, all the machines on the Pareto-optimal fronts are medium to high power machines (i.e. no machines with power rating below 20 HP).