Algorithm for optimal selection of drive motor transmission combination

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Keywords

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Abstract

For machine builders, it is essential to have an optimal balance between economic benefit and fulfillment of the technical requirements when selecting an appropriate driveline. This paper proposes a practical tool for finding the optimal drive-motor-transmission combination from a database of available devices. The algorithm denoted as the optimal selection tool consists of four main steps. The three first steps are dedicated to efficiently finding the triplets that meet the technical requirements and feasibilities (such as current-, torque-, speed- and ratio-limitations). The last step implements the branch and bound algorithm [1] to find the optimal solution in terms of price. The algorithm avoids unnecessary checks of not technically feasible combinations. This is possible because the motors and drives are sorted with ascending peak current and the transmissions with an ascending ratio in the database. The algorithm's utility is demonstrated in a validation example of a transfer robot (pick-and-place unit), where a drive-motor-transmission combination with the lowest possible price must be selected. This combination must fulfill the technical requirements. Because of the optimization, the possible 3276 combinations were reduced to 302 technically feasible combinations, which means a significant reduction of 90%. Furthermore, this reduction implies a decrease in computational load. After that, the fourth step selects the combination with the lowest price, which is 1668 units. This price is five times lower than the most expensive combination (8408 units).

Nomenclature

Parameter	Drive	Motor	Transmission
Symbol	d	m	g
Population size	r	h	k
Index	j	w	q
Cost	C_d	C_m	C_g
Peak current	I_{dp}	I_{mp}	-
Standstill current	I_{d0}	I_{m0}	-
Inertia	-	J_m	J_g
Peak torque	-	T_{mp}	-
Nominal torque	-	$T_{m_{nom}}$	-
Peak speed	-	n_{mp}	-
Ratio	-	-	i
Nominal speed	-	$n_{m_{nom}}$	-

- T_{lp} Peak load torque
- n_{lp} Peak load speed
- $J_{l_{max}}$ Maximum load inertia
- J_l Total load inertia
- i_{min} Minimum gear ratio
- i_{max} Maximum gear ratio
- T_{lv} Load torque reflected to the rotor, including the transmission
- n_{lv} Load speed reflected to the rotor, including the transmission
- $T_{lv_{RMS}}$ Root Means Square load torque reflected to the rotor, including the transmission
- N Number of samples
- b Best combination index

Introduction

One complex task in designing electric drivelines is selecting a proper drive-motor-transmission combination that allows driving the load with a specific motion profile, demanded torque, and speed. In addition, machine builders are also interested in solutions that contribute to economic benefits like price, weight, or energy consumption. Indeed, the authors in [2] proposed a method to find the best motor-transmission combination minimizing the power losses of the motor. In [3], the optimal combination for an exoskeleton is found by minimizing the power losses after eliminating non-feasible combinations based on motor and load characteristics. For machines where the component's weight plays an essential role, like an exoskeleton, an optimization can be performed under constraints in the weight of the motor-transmission set as proposed in [4].

Another interesting optimization is the determination of the optimal gear ratio for achieving maximum acceleration, as suggested in [5], [6], and [7]. Authors in [5] based the selection on price, where the best solution out of two motors for an industrial application is found. In [6], a normalized technique to compare different types of motors is presented. Then, the drive's current is minimized to get the combination with the lowest cost. The method presented in [7] minimizes the RMS torque by estimating the effect of the transmission on the other parameters like inertia and motor torque.

On the other hand, this paper aims to provide a tool for machine designers that finds the optimal combination of drive-motor-transmission from a database of commercially available devices that allows driving specific load inertia with a particular motion profile considering all elements simultaneously. Computational efficiency is essential when the available devices in the database increase. On that account, a procedure consisting of four steps is proposed. The three first steps are dedicated to find feasible triplets efficiently. Then, the last step consists of an optimization routine that minimizes or maximizes a specific cost function based on the so-called branch and bound algorithm [1].

Optimal selection tool

The optimal selection tool presented in this paper aims to find a suitable combination of drive, motor, and transmission. Therefore, the peak load torque (T_{lp}) and peak load speed (n_{lp}) are needed. In addition, a database with commercial drives, motors, and transmissions is used. The selection of a proper combination of drive-motor-transmission is challenging because it relies on finding an economical solution that can meet the application motion profile's load torque/speed requirements. Moreover, let r, h, and k be the drives', motor's, and transmission's population size. Then, the number of possible combinations is $(r \cdot h \cdot k)$, leading to a high computational effort to consider all these combinations. Therefore, the optimal selection tool consists of four main steps that reduce the possible combinations to a set of practical triplets and select the one that minimizes a specific objective function. These four steps are performed after sorting the motors and drives with ascending peak current while the transmissions are ordered by the ascending ratio (i). A summary of the optimal selection tool is depicted in the flow diagram in Fig. 1. Furthermore, the MATLAB® code is available upon request to the authors.

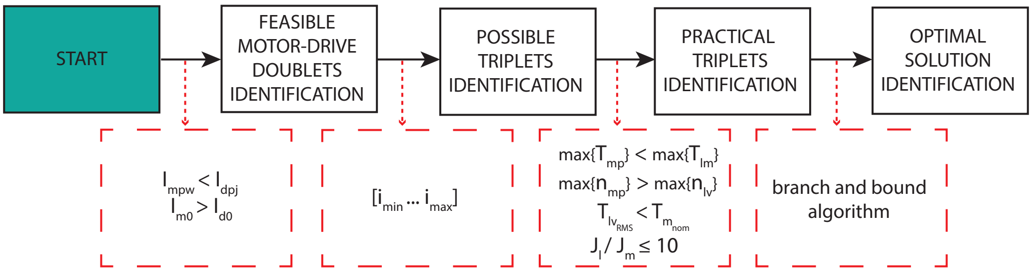

Fig. 1: Flow diagram of the optimal selection tool

Feasible drive-motor doublets identification

Not all drive-motor doublets are feasible from a technical point of view. One of the main reasons is that a driver has a specific current range delivered to the motor. As a consequence, the drive is not able to power all motors available in the database. To check which drive-motor doublets are feasible, the first step of the procedure takes advantage of the fact that the drives and motors are sorted from the lowest to the highest peak current (I_{dp}, I_{mp}).

This step is labeled as the feasible drive-motor doublets identification. The drive and motor indexes are represented as j and w. Hence, the algorithm starts selecting the motor with the highest peak current on the list ($I_{mpw}, w = h$) and compares it with all the drives starting from the one with the highest peak current ($I_{dpj}, j = r$), and decrements the drive selection j until the condition $I_{mpw} > I_{dpj}$ is met, as depicted in Fig. 2. The latter means neither the drive (j) can power the motor (w) nor can the remaining drives ($j-1, j-2, \cdots, 1$) in the list because they have a lower peak current. In that way, the number of checks is minimal. The algorithm does the same for all list's motors ($w = h$ to 1), and the output is a list of feasible drive-motor doublets. Furthermore, the standstill current of the motor (I_{m0}) must be higher than the standstill permissible current of the drive (I_{d0}). This condition is checked for the identified doublets.

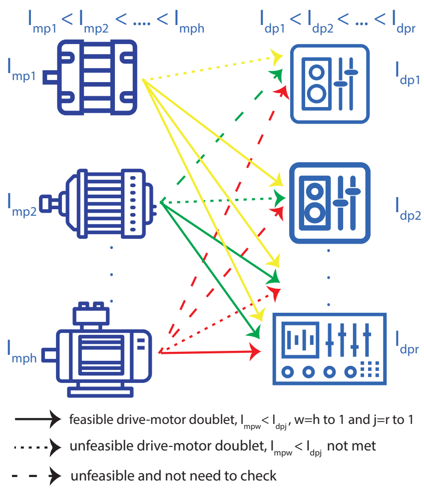

Fig. 2: Feasible drive-motor doublets identification

A reduction of combinations is achieved through the doublets identification step that only considers the drives and motors. However, including transmissions in the tool requires checking each doublet and database's transmission, leading to a list of triplets.

Possible triplets identification

The remaining steps of the optimal selection algorithm require the explanation of some functions and variables that are employed. First, the load torque and speed are defined by a trajectory with multiple samples (N) taken at a specific sample instant (t). They are defined as ($T_{lp}[t]$), and ($n_{lp}[t]$), where $t = 1, 2, \cdots, N$. These quantities can be defined graphically through the (N) samples ($n_{lp}[t], T_{lp}[t]$) represented by the red curve depicted in Fig. 3 (left). Furthermore, the torque-speed curves for commercial motors are available in the datasheet or provided by the manufacturer. In this paper, the peak and nominal torque-speed curves are relevant. The former characterizes the motor's peak capacity, and the latter is related to the nominal motor's operation. There are also many samples taken at time instant (u) for these curves, which size is not necessarily equal to (N). Thus, both curves are formed by the samples ($n_{mp}[u], T_{mp}[u]$) and ($n_{m_{nom}}[u], T_{m_{nom}}[u]$). The last function to define is the load torque after including the transmission, represented in (1):

$$T_{lv}[t] = \frac{T_{lp}[t]}{i} + (J_m + J_g) \cdot \ddot{\theta}[t] \cdot i, \tag{1}$$

where $\ddot{\theta}$ refers to the load acceleration. It can be seen from (1) that the expression is computed from $T_{lp}[t]$; therefore, it contains the same number of samples (N). In addition, the load torque after considering the transmission can be represented graphically in the same way as the load torque through the pairs ($n_{lv}[t], T_{lv}[t]$), where ($n_{lv}[t] = i \cdot n_{lp}[t]$) is the reflected load speed.

On the other hand, the second step of the optimal selection tool, the so-called possible triplets identification, consists of selecting the viable range of gear ratio for the feasible drive-motor doublets based on the load torque ($T_{lp}[t]$) and speed ($n_{lp}[t]$)). Then, only the transmissions inside the correct range are considered. The minimum gear ratio (i_{min}) and maximum ratio (i_{max}) are computed for every feasible drive-motor doublet. The minimal gear ratio (i_{min}) is obtained by dividing the maximum value of the peak load torque (T_{lp}) by the maximum motor peak torque (T_{mp}) as represented by (2)

$$i_{min} = \frac{max\{T_{lp}[t]\}}{max\{T_{mp}[u]\}} \tag{2}$$

The above means that the necessary ratio to reach the maximum peak load torque is given by i_{min}. Likewise, the maximum peak motor speed is divided by the maximum peak load speed to determine the maximum ratio (3), which can be interpreted as the highest transmission ratio that allows fulfilling the load speed.

$$i_{max} = \frac{max\{n_{mp}[u]\}}{max\{n_{lp}[t]\}} \tag{3}$$

The graphical description of the procedure is depicted in Fig. 3 (left). Furthermore, the algorithm searches into the database for the transmissions with the minimum and maximum ratio inside the range $[i_{min} \cdots i_{max}]$. Then, it assigns a starting and ending transmission index (q) for each motor belonging to the doublets. Consequently, the possible triplets are obtained by paring the doublets with the transmissions between the starting and ending index (q).

Practical triplets identification

The third step of the optimal selection tool is denoted as practical triplets identification. In addition, four conditions can be performed to reduce the number of possible triplets. The first condition consists of checking that the maximum value of the motor's peak torque ($max\{T_{mp}[u]\}$) is higher than the maximum value of the peak load torque reflected to the rotor after including the transmission ($max\{T_{lv}[t]\}$). The second condition states that after including the transmission inertia, the maximum value of the peak load speed ($max\{n_{lv}[t]\}$) must be lower than the maximum value of the peak motor's speed ($max\{n_{mp}[u]\}$). In the third condition, the Root Mean Square (RMS) reflected load torque ($T_{lv_{RMS}}$) must be lower than the nominal torque of the motor ($T_{m_{nom}}[u]$) at the mean load speed[1] ($\bar{n_l}$). Finally, the last condition verifies that the inertia ratio between the total load and the motor's rotor must be lower or equal to ten, as suggested

[1] Statistical mean computed as $\bar{n_l} = \frac{1}{N}\sum_{t=0}^{N} n_{l_v}[t]$

in [8]. In this case, the total load inertia is composed of the maximum load's inertia reflected to the motor shaft and the transmission's inertia, as indicated in (4).

$$J_l = \frac{J_{l_{max}}}{i^2} + J_g \tag{4}$$

After checking the previous conditions, the practical triplets identification is performed for the resulting possible triplets. As shown in Fig. 3 (right), the algorithm checks that the load torque after including the transmission ($T_{lv}[t]$) is lower than the motor peak torque[2] ($T_{mp}[t]$) for all operation points or samples (N). If the condition is not met, the algorithm stops, and the triplet is discarded. In that way, the output is the practical triplets.

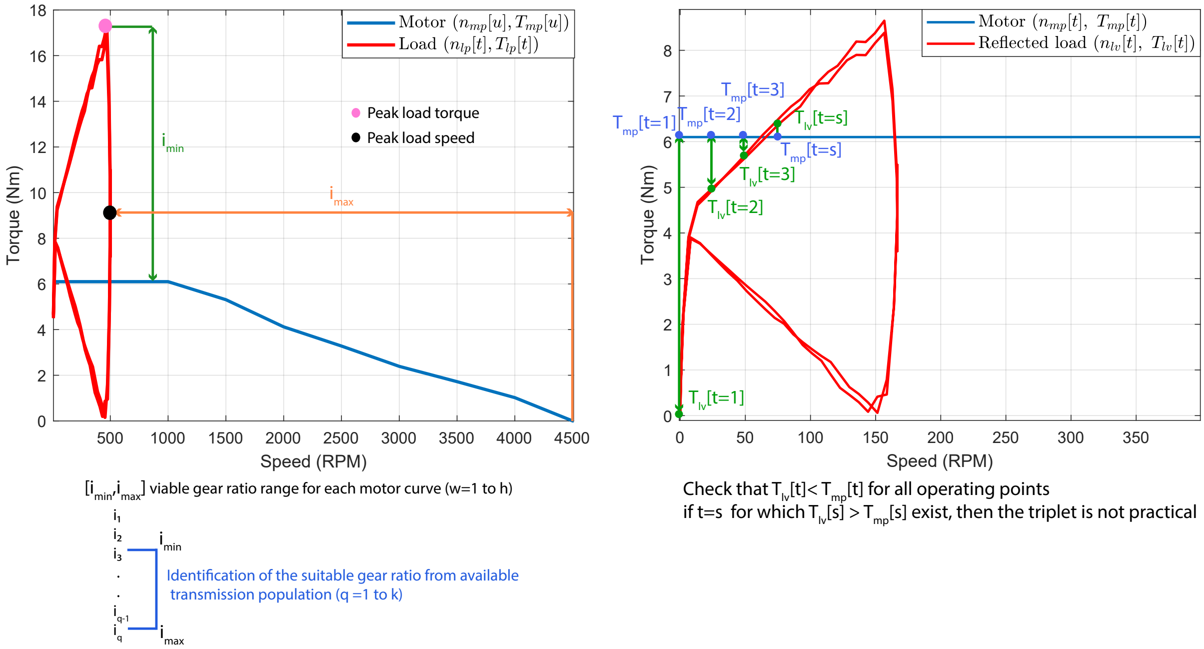

Fig. 3: Viable gear ratio for available motors (left). Practical triplets identification based on load torque (right)

Optimal solution identification

The optimal solution identification step aims to find the optimal triplet from the available practical triplets. For that, the objective function C_b must be minimized. This objective function can be computed in three different ways; only the drive's price, the combination of drive-motor prices, or even the addition of all combination's elements prices (drive-motor-transmission)[3]. On that account, from this point in this manuscript, the objective function C_b will be referred to as the actual best price. The so-called branch and bound algorithm [1] is used for solving this problem.

The mentioned algorithm searches efficiently for the triplet with the lowest price. The strategy is to discard as many unnecessary checks as possible. The way the algorithm achieves discarding combinations is to check progressively. The latter can be illustrated through some steps of the algorithm. One of the steps checks that the ongoing drives' price is lower than the price of the actual best combination. If the condition is not met, all triplets containing the current drive can be discarded, contributing to substantially reducing operations. On the contrary, the algorithm goes to the next step if the condition is met. Here, the price of the drive-motor combination is compared with the actual best combination. If

[2] $T_{mp}[t]$ is obtained from the linear interpolation of $T_{mp}[u]$

[3] The units of the objective function are arbitrary and not related to any currency, so it is only illustrative

the current drive-motor price exceeds the price of the actual best combination, all triplets containing the drive-motor can be discarded, also reducing operations. The complete flow diagram of the algorithm is depicted in Fig. 4.

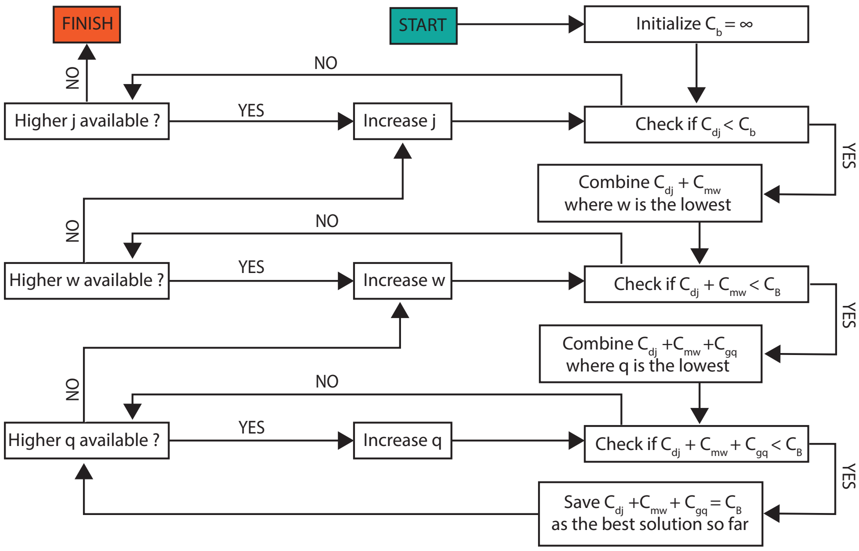

Fig. 4: Branch and bound algorithm for finding the optimal drive-motor-transmission triplet

Finally, it is relevant to mention that the objective function C_b can be extended to consider other relevant factors that machine builders are interested in optimizing, e.g., total losses, weight, and size, among others. For instance, the necessary modification to the optimal solution identification step is twofold. First, the relevant factors have to be normalized using their highest value. Second, the objective function C_b is built from the sum of those weighted factors, where the wights allow for prioritizing some factors over others.

Validation Case

This section aims to validate the functionality of the optimal selection tool. Therefore, a machine builder provides the load torque, speed, and acceleration of a transfer robot installed in a manufacturing cell performing repetitive movements to apply the proposed algorithm. The robot's task is to take an object from one position and place it on a conveyor belt on the other side of the production line. The manufacturer is interested in the drive-motor-transmission with the lowest possible price to drive a payload with the specific torque, speed, and acceleration profiles from Fig. 5. The algorithm is implemented in MATLAB®. In this case, a database with $r = 6$ drives, $h = 21$ motors, and $k = 26$ transmissions is used resulting in $(6 \cdot 21 \cdot 26 = 3276)$ possible combinations. The number of combinations at each step for the transfer robot is shown in Fig. 6. It is relevant to mention that the only motor technology considered in the validation case is the permanent magnet synchronous machine (PMSM).

For this example, the number of allowable drive-motor combinations is the product $(r \cdot h = 126)$. However, after applying the feasible drive-motor doublets identification step, feasible doubles are the 36 shown in Table I. Furthermore, the total number of possible triplets is obtained by multiplying feasible drive-motor doublets and the total number of transmissions, resulting in $(36 \cdot 26 = 936)$. On that account, after applying the first step of the algorithm, the total number of possible triplets $(6 \cdot 21 \cdot 26 = 3276)$ is reduced to around one-third. In addition, the possible triplets identification step is applied. As a result, the starting and ending index for the transmissions for each feasible drive-motor doublet can be observed in the fourth, fifth, ninth, tenth, fourteenth, and fifteenth columns from Table I.

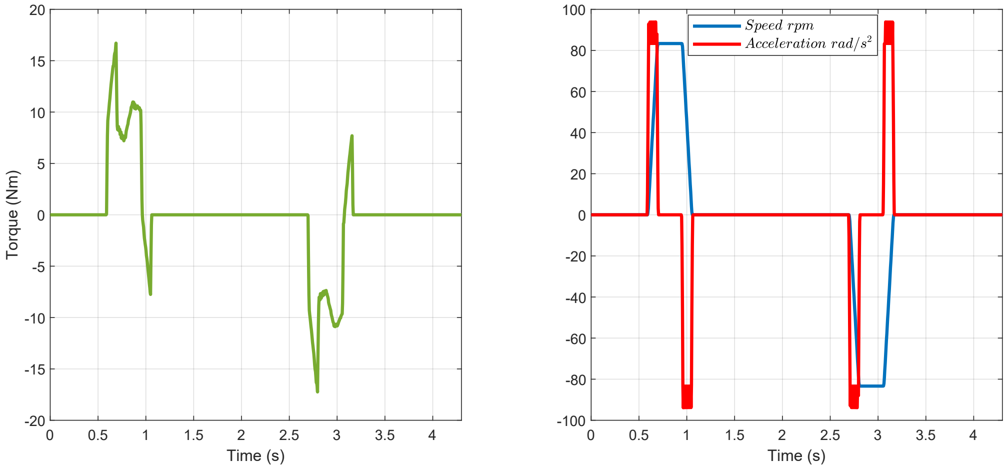

Fig. 5: Torque (left), speed and acceleration (right) required for the transfer robot

The interpretation of the latter can be explained with an example. Considering the left part of the first row from Table I, which corresponds to the first feasible drive-motor doublet, the triplets formed by considering only the transmission with index one until the transmission with index eleven are the possible triplets for the specific feasible doublet. The advantage of this step is clear at this point because for this feasible doublet, only 11 transmissions out of the 26 are worth checking, and the number of operations is reduced. Finally, the possible triplets for the transfer robot (650) are formed by adding all the feasible doublets from Table I.

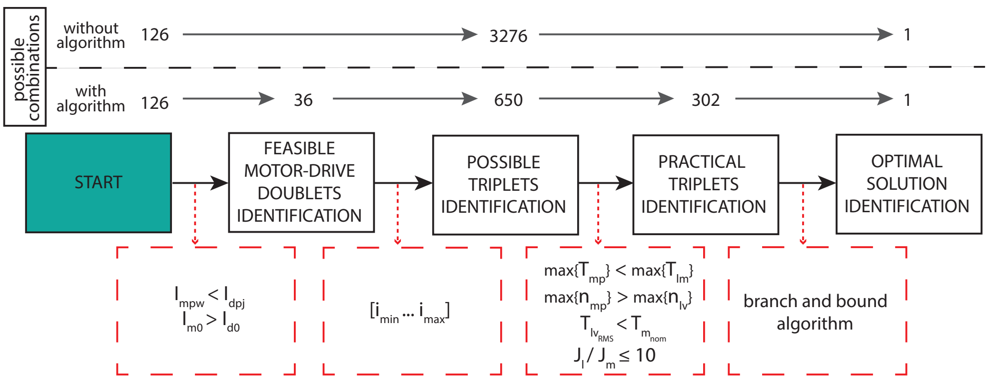

Fig. 6: Flow diagram of the optimal selection tool for the transfer robot including the number of combinations with and without algorithm

To continue with the practical triplets identification step, first the condition $(max\{T_{mp}[u]\} > max\{T_{lv}[t]\})$ is checked for the possible triplets, leading to (617) triplets. Furthermore, conditions $(max\{n_{mp}[u]\} > max\{n_{lv}[t]\})$ and $((\bar{n}_l, T_{m_{non}}) > (\bar{n}_l, T_{lv_{RMS}}))$ are applied, resulting in 564 triplets fulfilling both requirements. Finally, the condition $(J_l/J_m \leq 10)$ is verified. As a result, the number of possible triplets is reduced to 328. The above intermediate steps are justified after considering the number of operations that the optimal selection tool requires in the practical triplets identification step. In this case, the speed profile contains $(N = 1001)$ samples, which in the case of the possible initial triplets takes $(1001 \cdot 650 = 650650)$ checks as in Fig. 3 (right). Instead, if the possible triplets after applying the intermediate conditions are used, the number of necessary checks is $(1001 \cdot 328 = 328328)$, which saves (322322) operations. In this example, (26) triplets from the (328) possible drive-motor-transmission triplets do not fulfill the condition $T_{lv}[t] < T_{mp}[t]$ for all (N) samples, which implies that (302) are the practical triplets.

Table I: Doublets for the transfer robot

Index	**j**	**w**	**S q** [4]	**E q** [5]	**Index**	**j**	**w**	**S q**	**E q**	**Index**	**j**	**w**	**S q**	**E q**
1	6	4	1	11	13	5	5	12	23	25	5	1	11	24
2	6	7	1	23	14	1	13	2	26	26	1	14	2	21
3	1	6	1	26	15	5	13	2	26	27	5	14	2	21
4	1	2	2	24	16	1	20	2	26	28	1	11	8	23
5	1	17	1	21	17	5	20	2	26	29	5	11	8	23
6	1	16	2	26	18	1	19	2	26	30	1	10	7	26
7	5	16	2	26	19	5	19	2	26	31	5	10	7	26
8	1	3	2	23	20	1	9	2	26	32	4	10	7	26
9	5	3	2	23	21	5	9	2	26	33	1	21	10	24
10	1	12	4	23	22	1	18	2	24	34	4	21	10	24
11	5	12	4	23	23	5	18	2	24	35	1	15	12	26
12	1	5	12	23	24	1	1	11	24	36	4	15	12	26

Table II: Specification optimal solution (left). Specification second-best solution (right)

Optimal solution				**Second-best solution**			
Motor		**Drive**		**Motor**		**Drive**	
T_{mp}	$2.67\ Nm$	I_{dp}	$13\ A$	T_{mp}	$6.36\ Nm$	I_{dp}	$13\ A$
$T_{m_{nom}}$	$0.5\ Nm$	I_{d0}	$1\ A$	$T_{m_{nom}}$	$1\ Nm$	I_{d0}	$1\ A$
$n_{m_{nom}}$	$9000\ rpm$	C_d	840 units	$n_{m_{nom}}$	$8000\ rpm$	C_d	840 units
J_m	$0.134\ kgm^2$	**Transmission**		J_m	$0.373\ kgm^2$	**Transmission**	
I_{mp}	$8.6\ A$	Ratio	40	I_{mp}	$11.4\ A$	Ratio	40
I_{m0}	$1.6\ A$	J_g	$0.35\ kgcm^2$	I_{m0}	$2.2\ A$	J_g	$0.35\ kgcm^2$
C_m	320 units	C_g	710 units	C_m	382 units	C_g	710 units

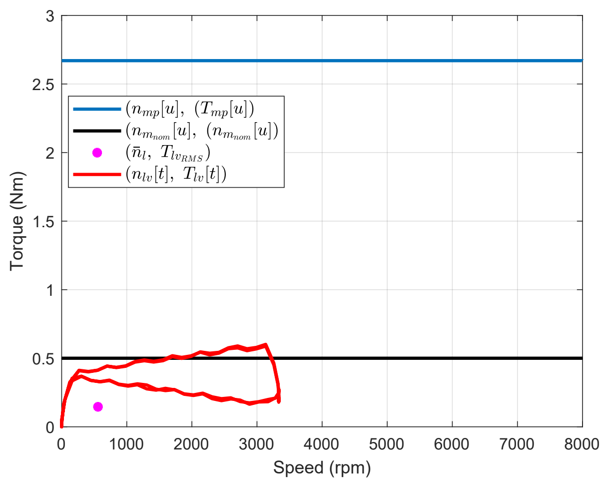

Fig. 7: Speed-torque curves for the optimal solution reflected load and motor

[4] Starting q index
[5] Ending q index

Finally, the optimal solution identification step allows finding the triplet with the lowest price of the 302 practical triplets. Instead of checking the 302 triplets, the necessary number of checked triplets is reduced to 191 based on the branch and bound algorithm described in the optimal solution identification step. The optimal solution parameters are indicated in Table II (left), and the comparison between the motor curves and the application curve for the optimal solution is depicted in Fig. 7. The magenta point represents $(\bar{n}_l, T_{lv_{RMS}})$ for the optimal solution. The second-best solution information is presented in Table II (right) to compare both solutions. It can be observed that the drive and transmission are the same, but the motor is different. Therefore, the motor is the critical element because the second-best triplet uses a motor with higher torque which is more expensive. Consequently, the price leads to a difference of around 60 units related to the best solution.

Conclusion

The optimization tool presented in this paper identifies the most cost-efficient drive-motor-transmission triplet for machine builders when an extensive database of devices is available. The first three steps of the algorithm reduce the initial number combinations $(r \cdot h \cdot k)$ to a limited number of practical triplets, as demonstrated with the validation case where the initial 3276 combinations were reduced to only 302 practical triplets. In addition, the optimization algorithm found the optimal solution efficiently instead of checking all the 302 practical triplets. Finally, to outline the scope of the optimal selection tool, it is relevant to compare the price of the best and the most expensive practical triplet. The drive, motor and transmission prices of the most expensive triplet are 3328, 2190, and 2890 units, respectively. The total price is 8408 units compared to the optimal triplet total price of 1668 units. Therefore, it is clear that even though both solutions are technically feasible, the optimal selection tool identifies a solution with a saving factor of five.

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