Development and validation of a CFD based optimization procedure for the design of torque converter cascade

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ABSTRACT

Traditional one-dimensional (1D) design theory no longer satisfies modern torque converter design requirements due to the lack of accuracy and long trial-and-error process. A computational fluid dynamics (CFD) based optimization approach was brought forward. This study is devoted to two key processes in bringing CFD into torque converter design – blade parameterization/evaluation and optimization. A six-parameter blade camber line design method was employed to represent the blade shape. The blade profile was evaluated based on manufacturability considerations. A low-fidelity CFD model was developed for parameter study and optimization, and a high-fidelity CFD model considering the transient and cavitation effects was employed to evaluate the optimization outcome. The parameter sensitivity study was performed using design of experiment (DOE) technique and the variables were categorized into primary design variable, effective design variable and insignificant design variable groups. Optimization on the primary variables was carried out using the genetic algorithm. Two optimum solutions were evaluated with the transient full 3D CFD model and then tested. The optimum torque converters' test results indicated significant performance improvement. The proposed design procedure can improve the design efficiency & accuracy and shorten the design cycle by the application of different CFD models in conjunction with an optimization algorithm.

1. Introduction

A torque converter is a fluid coupling device which transfers power through the interaction of moving fluids and cascades. Torque converters are wear-free and are capable of absorbing vibration from the input sources and providing torque amplification. Thus, torque converters are widely used in vehicle transmissions and industrial power transmissions. It consists of a pump, which is driven by a prime mover, a turbine, which is connect to the working machine and a stator, which is fixed to the transmission case (Liu, Liu, & Ma, 2015). The blade shape is highly twisted and the internal flow is highly turbulent, which makes the design of torque converters a complex procedure.

The traditional textbook design theory simplifies the complex three-dimensional fluid flow into a one-dimensional stream and omits the viscous and turbulent effects, leading to poor accuracy and suboptimal solutions. With the development of computational fluid dynamics (CFD) and rapid increase of computing power, the CFD-based optimization (CFD-O) has become practical and more often adopted in engineering applications (e.g. Ezhilsabareesh, Rhee, & Samad, 2018; Fu, Shi, Deng, Li, & Feng, 2012; Song & Liu, 2018). The searching direction is guided by optimization algorithms. Various optimization algorithms were introduced and performed on real-world engineering cases. The gradient based algorithm, evolutionary algorithm and artificial intelligence are all very popular (Fotovatikhah et al., 2018; Tengs, Storli, & Holst, 2018). The practical limit for the application of CFD-O is the conflict between the high computing power required by CFD and the large number of design evaluations required by optimization. Generally, real optimization problems found in turbomachinery cascade design involve too many design variables and several performance objectives, which would require a tremendous amount of design evaluations to achieve the optimized solutions. The solution for this contradiction is clear: First the evaluation process must be sped up and second the number...
of required evaluations must be reduced. Simplifying the physical model would greatly speed up the evaluation process (Elfert et al., 2017; Meyer, Daroczy, & Thevenin, 2017). Periodic assumptions were also generally used in CFD-O design process (Jaron, Moreau, Guerin, & Schnell, 2018; Kragic, Vucina, & Milas, 2018; Kragic, Vucina, & Milas, 2016). The application of appropriate approximation would lead to a drastic reduction of CFD evaluations (Bamberger & Carolus, 2017; Bargiel, Kostowski, Klimanek, & Gorny, 2017; Liang, Cheng, Li, & Xiang, 2011). The adjoint method may also decrease the function evaluations needed for optimization (Dhert, Ashuri, & Martins, 2017). Different models could be used to speed up the optimization process while maintaining the accuracy of the solutions. Wu, Shimmei, Tani, Niikura, & Sato (2007) built a CFD-based design system with both rapid CFD and elaborated CFD models for hydro turbines. The result indicated pronounced improvement in terms of efficiency and power density after the optimization.

Research work can also be found on the application of CFD-O technique in the torque converter cascade design process. Liu, Untaroiu, Wood, Yan, and Wei (2015) analyzed the parameter sensitivity of torque converter inlet deflection angles, and optimized the performance using a single passage torque converter model in conjunction with multi-objective genetic algorithm. Song, Kim, Park, Kook, and Oh (2008) integrated and automated the complex design process involving CFD simulations into a torque converter design platform. The platform was able to obtain an optimized torque converter geometry at 1/30 the man-hour cost compared to the traditional method. Wei and Yan (2009) proposed a torque converter integrated design optimization system which allowed for the optimization search on the response surface derived from CFD design evaluation results. However, the previous research work focused either on some certain parameters (Liu, Pan, Yan, & Wei, 2012; Liu et al., 2015) or on the integration of the design process (Song et al., 2008; Wei & Yan, 2009). The present work is devoted to two core issues regarding the conflict of applying CFD-O technique to torque converter design – the blade parameterization and the optimization procedure. Blade parameterization has a significant effect on the design flexibility and efficiency. Treating the blade profile by its control points is not practical because that would lead to excessive degrees of freedom and thus requires prohibitive computing power (Derksen & Rogalsky, 2010). In order to present the torque converter blade profile in an effective and efficient manner, a blade camber line parameterization based on Bezier curves is used. Blade shape evaluation methods regarding manufacturability were put forward. Then the design parameters were identified and split into subgroups based on design of experiment (DOE) study. A multi-objective optimization algorithm was then implemented to search for Pareto solutions based on a fast and low-fidelity CFD model, and the selected results were evaluated by a transient high-fidelity CFD model considering more physics. Finally, a base torque converter was evaluated and optimized. Two selected optimal solutions were manufactured and tested. This study presents a practical torque converter design approach based on CFD simulations. The design accuracy and efficiency are substantially improved by the application of CFD evaluation. The parameter screening approach and the utilization of different CFD models are able to shorten the design cycle substantially.

2. Methodology

2.1. CFD-based blade design system

The CFD-based blade design procedure is illustrated in Figure 1. First, design variables are evaluated by DOE in conjunction with a fast CFD model. The purpose of DOE is to identify primary design variables and to sort the design variables into various sub-group based on their significance level. Then a multi-objective evolutionary algorithm is utilized to explore optimum solutions on the fast CFD model. Finally, the selected solutions are evaluated by an accurate CFD model which is able to provide precise predictions by considering transient interaction, boundary layer treatment and cavitation (multi-phase). If the performance requirements are not met, then return to the optimization process and add additional parameters as input variables to expand the design space. The optimization process will be repeated until satisfactory solutions are achieved.
Figure 2. Integrated fast CFD evaluation platform.

The DOE and optimization are performed on an integrated CFD design system, as shown in Figure 2. The blade profile is calculated in Matlab and imported into TurboGrid for periodic flow passage generating. The flow passage mesh is then created in ICEM-CFD and imported into ANSYS CFX™ for fluid field simulation. The design vector is controlled by either DOE or optimization and all the design process was integrated in Isight™. It is worth noting that the blade profile is evaluated based on manufacturability constraints and the failed samples will be treated as an error. By doing this, unnecessary CFD simulations can be prevented to improve design efficiency.

2.2. Blade parameterization and shape evaluation

Two joint Bezier curves - the leading Bezier curve and the trailing Bezier curve - were employed to construct the blade camber line. The thickness distribution was formulated by an empirical equation according to camber line shape. The detailed camber line model can be found in Liu, Wei, Yan, and Morgan (2017a), and the variables were shown in Table 1 and Figure 3.

The blade shape is evaluated based on manufacturability. One basic constraint is that the camber line should not contain any loop, which would occur at the joint under certain parameter combinations. Thus, the following constraints should be applied to the control point coordinates:

\[
\begin{align*}
\alpha_i &> \tan^{-1}\left(\frac{y_p}{x_p}\right) \\
\alpha_o &> \tan^{-1}\left(\frac{y_p}{1-x_p}\right)
\end{align*}
\]

Figure 3. Blade camber line geometry and parameters (a) unit camber line and (b) actual camber line.

Table 1. Blade parameters.

| Parameter                        | Symbol | Unit  |
|----------------------------------|--------|-------|
| Actual meridional length         | \( L \) | mm    |
| Leaning angle                    | \( \psi \) | °     |
| Inlet wedge angle                | \( \alpha_1 \) | °     |
| Unit camber peak position        | \( x_p \) | –     |
| Unit camber peak                 | \( y_p \) | –     |
| Unit curvature at the juncture   | \( \rho_p \) | –     |
| Outlet wedge angle               | \( \alpha_o \) | °     |

where the subscript \( l \) and \( t \) represent the leading curve and trailing curve, respectively, and the subscript 1 and 2 denote the sequence from the start point to the end point. Another important constraint regarding both manufacturability and hydrodynamic performance is that the blade camber line should not be concave. As shown in Figure 4, small inlet or outlet wedge angle would inflect the blade camber line, leading to blade profiles that could not be manufactured. The following constraints can be used to filter out such camber lines.
Concave blade camber line example with (a) small inlet wedge angle and (b) small outlet wedge angle.

Figure 4. Concave blade camber line example with (a) small inlet wedge angle and (b) small outlet wedge angle.

Figure 5. Blade pressure side loop example.

The inlet wedge angle \( \alpha_i \) and outlet wedge angle \( \alpha_o \) are replaced by corresponding coefficients – \( \tau_i \) and \( \tau_o \), respectively. Therefore, the constraint can be easily imposed as \( \tau_i, \tau_o > 1 \):

\[
\begin{align*}
\tau_i &= \frac{\alpha_i}{\tan^{-1} \left( \frac{y_p}{x_p} \right)} \\
\tau_o &= \frac{\alpha_o}{\tan^{-1} \left( \frac{y_1}{1-x_p} \right)}
\end{align*}
\tag{3}
\]

If the blade camber line is highly twisted at the juncture with small curvature and the thickness is also high at the corresponding area, it may create a loop in the pressure side of the blade profile, as shown in Figure 5. So the blade pressure side data is checked to make sure there is no loop.

The final constraint is there should be no intersection between blades. When the blade leaning angle \( \varphi \) or blade count \( N \) is too high, the blade profiles may intersect with each other. The minimum distance between adjacent blade \( \Delta_{\text{min}} \) is calculated to make sure there are no intersections (Figure 6). In order to leave enough space for the cascade casting, the following constraint is applied:

\[
\Delta_{\text{min}} > 2 \text{ mm} \tag{4}
\]

Only the profiles that satisfy all constraints proceed to the CFD simulation procedure. The failed samples will be treated as an error and skip the CFD calculation to improve design efficiency.

2.3. Parameter study based on DOE

Six parameters – \( \tau_i, \tau_o, x_p, y_p, \rho_p \) and \( \varphi \) – are required to define the blade profile shape, and two additional parameters – entrance bias angle \( \gamma \) and blade number \( N \) – are required to design the cascade. The simplest torque converter contains three components, which means at least 24 design variables should be considered in torque converter design process. Such a large design variable pool would cause the problem of dimensionality and requires prohibitive computing effort to search for optimum solutions. Parameter study should be performed before optimization to determine the effects and chose design variables accordingly.

The blade shape parameters was evaluated by DOE on each component. The design matrix was determined by the optimized Latin hypercube sampling method to get evenly distributed samples. The samples were evaluated by the integrated fast CFD evaluation platform and the responses were analyzed by the following cubic polynomial model:

\[
y = \beta_0 + \sum_{j=1}^{n} \beta_j x_j + \sum_{j=1}^{n} \beta_{jj} x_j^2 + \sum_{j=1}^{n} \beta_{jjj} x_j^3
\]
\[ + \sum \sum_{i<j} \beta_{ij} x_i x_j + \sum \sum_{i<j} \beta_{ij} x_i^2 x_j + \sum \sum_{i<j<k} \beta_{ijk} x_i x_j x_k + \epsilon \]  

(5)

where main effect, quadratic and cubic curvature effects, two-factor interaction and three-factor interaction effects are included. Then the significance of each effect as well as the model was evaluated by analysis of variance (ANOVA). ANOVA is a powerful statistical tool to determine the significance of a regression model and test for differences between means.

The responses considered herein are stall torque ratio \((TR_0)\), stall capacity constant \((C_0)\) and maximum efficiency \((\eta_{\text{max}})\), which indicate the launching performance, power density and economy characteristics of torque converters, respectively. Pressure distribution can be determined by CFD analysis, then the overall torque of each component can be derived and the responses are calculated as follows:

\[
\begin{align*}
TR_0 &= \frac{TT_0}{TP_0} \\
C_0 &= \frac{TP_0}{\omega_P^2 D^5} \\
\eta_{\text{max}} &= \max \left( \frac{n_T \times TT}{n_P \times TP} \right)
\end{align*}
\]

\[(6)\]

where \(TT\) and \(TP\) denote turbine torque and pump torque, respectively, \(n_T\) and \(n_P\) (\(\omega_P\)) indicate turbine rotational speed and pump rotational speed, respectively, \(D\) is torus diameter. Subscript ‘0’ represents stall operating condition.

The significance of each model and effect was evaluated by ANOVA, then the responses were built based on a 95% significance level. A reduced model was built by removing the effects with \(P\)-value higher than 0.05 regardless of model hierarchy.

### 2.4. CFD modeling

Two CFD models were adopted in the torque converter design procedure – the fast CFD model and the accurate CFD model. The basic settings for these two models are listed in Table 2 and the model examples are illustrated in Figure 7. The pump was fixed at 2000 rpm, and the stator is held stationary. The turbine speed was varied from 0 to 1600 rpm at 200 rpm interval in order to simulate various speed ratios \((SR = n_P/n_T)\). The torque converter is a closed-loop turbomachinery; thus no inlet or outlet boundary conditions are applied. Rotationally periodic boundaries were applied to the periodic surfaces of each domain in the fast CFD model. Besides, stage interface model was utilized to transfer data between adjacent domains for the steady-state fast CFD calculations. As for transient CFD calculations, transient rotor-stator model was applied to the interface and the mass transfer process induced by cavitation was considered.

![Figure 7. CFD model for (a) single flow passage and (b) full flow passage.](image)
Figure 8. Grid independence study results for (a) periodic model and (b) full model.

effect. Additionally, SST turbulence model was employed in the accurate CFD simulation to better capture near-wall flow and flow separation behavior. Cavitation occurs when local pressure drops below saturation pressure and brings severe hydrodynamic performance degradation (Liu et al., 2017a). The transient cavitation process was governed by Rayleigh–Plesset equation, and homogeneous model was applied to simplify the calculation. The saturation pressure was set to be 110 Pa and the initial bubble radius of $1\times10^{-6}$ m was assumed (Liu, Wei, Yan, & Weaver, 2017b). The grid independence study for both CFD models was illustrated in Figure 8. The results show that the fast CFD model requires around half a million elements to limit the variance to within 3%, whereas the accurate CFD model needs around ten million elements. The mesh for the accurate CFD model was further refined and a 12-layer prism grid was generated around each blade (Figure 7), leading to sufficiently low $y^+$ values for the implementation of low-Re formulation. The typical calculation time was around 0.5 and 82 h (1000 time steps) for the fast CFD model and accurate model, respectively. The calculation was performed using five nodes (20 cores per node with 128 GB memory) of Rivanna, the high-performance computing system located at University of Virginia.

2.5. Optimization algorithms

Various heuristics-based multi-objective optimization techniques were compared on the optimization of torque converter cascade, and it was suggested that archive based micro genetic algorithm (AMGA) should be used on non-constrained problems, whereas non-dominated sorting genetic algorithm (NSGA-II) outperforms others on constrained problems (Liu, 2015).

By introducing a new selection procedure based on a large number of archived elite solutions, AMGA is able to converge to Pareto-front with relatively small number of function evaluations (Tiwari, Koch, Fadel, & Deb, 2008). NSGA-II performs well in handling constraints due to the application of the constrained-domination principle, and it is able to maintain a wide spread of solutions and a good searching ability using a fast non-dominated sorting procedure (Deb, Pratap, Agarwal, & Meyarivan, 2002). The recommended parameter settings for the algorithms are crossover probability = 0.95, mutation probability = 0.02, crossover distribution index = 10 and mutation distribution index = 20. The presented settings are able to accomplish a proper balance between exploration and exploitation ability of the algorithms.

3. Results and validation

3.1. Parameter study

The base model is a 400 mm torque converter. The design parameters for each component were firstly investigated using DOE. The statistically significant variables were detected and the significance levels were determined by ANOVA. The torus dimensions remain unchanged. The initial variables/bounds as well as the performance for the base model are listed in Table 3. The variables were varied to the most feasible extent in terms of manufacturability to enlarge the design space as much as possible (Liu, 2015).

In order to fit a cubic equation considering interactions (Equation (5)) with eight variables, at least 165 samples are required. Herein 500 samples were generated using optimized Latin hypercube sampling to ensure that enough degrees of freedom were provided for error analysis and ANOVA. The full cubic model was first generated and evaluated, then the reduced model was built by removing insignificant effects with $p$-value higher than 0.05. Coefficient of determination ($R^2$) and adjusted coefficient of determination (Adjusted $R^2$) were determined.
Table 3. Baseline model variables and hydrodynamic performance

| Design variables | $\tau_i$ | $\tau_o$ | $\psi$ (°) | $x_p$ | $y_p$ | $\rho_p$ | $\gamma$ (°) | $N$ |
|------------------|---------|---------|-----------|------|------|--------|------------|----|
| **Pump**<br>B1  | 1.64    | 1.82    | 30.7      | 0.592| 0.095| 10.2   | 47.18      | 22 |
| L1               | 1.05    | 1.05    | -4        | 0.2  | 0.05 | 0.5    | -20        | 10 |
| U1               | 3       | 3       | 45        | 0.8  | 0.45 | 50     | 60         | 35 |
| **Turbine**<br>B1| 1.68    | 1.53    | 29.2      | 0.291| 0.35 | 0.8    | 0.15       | 24 |
| L1               | 1.05    | 1.05    | -4        | 0.2  | 0.05 | 0.5    | -30        | 10 |
| U1               | 3       | 3       | 45        | 0.8  | 0.45 | 50     | 40         | 35 |
| **Stator**<br>B1 | 1.59    | 1.22    | -37.9     | 0.36 | 0.199| 29.7   | 0.04       | 20 |
| L1               | 1.05    | 1.05    | -4        | 0.2  | 0.05 | 0.5    | -30        | 10 |
| U1               | 3       | 3       | 45        | 0.8  | 0.45 | 50     | 40         | 35 |

Experimental hydrodynamic performance

| $TR_0$ | $C_0$ (kg m$^{-3}$) | $\eta_{\text{max}}$ (%) |
|--------|---------------------|------------------------|
| 2.35   | 2.40                | 83.3                   |

Table 4. ANOVA results for cubic model.

| R² | Adjusted R² |
|----|-------------|
| Full model | Reduced model | Full model | Reduced model | Factors with insignificant main effect |
| Pump | $TR_0$ | 0.997 | 0.996 | 0.995 | 0.996 | $\rho_p$, $x_p$, $\tau_i$ |
| C₀ | 0.997 | 0.997 | 0.996 | 0.996 | $\rho_p$, $\tau_i$ |
| $\eta_{\text{max}}$ | 0.964 | 0.953 | 0.945 | 0.951 | $\rho_p$, $x_p$, $\tau_i$ |
| Turbine | $TR_0$ | 0.971 | 0.968 | 0.961 | 0.964 | $\rho_p$, $\tau_i$ |
| C₀ | 0.961 | 0.954 | 0.947 | 0.95 | $\rho_p$, $\tau_i$ |
| $\eta_{\text{max}}$ | 0.954 | 0.948 | 0.938 | 0.941 | $\rho_p$ |
| Stator | $TR_0$ | 0.984 | 0.975 | 0.954 | 0.958 | $\rho_p$, $\tau_i$ |
| C₀ | 0.962 | 0.953 | 0.943 | 0.948 | $\rho_p$, $\tau_i$, $\tau_o$ |
| $\eta_{\text{max}}$ | 0.951 | 0.947 | 0.941 | 0.946 | $\rho_p$, $\tau_i$ |

by ANOVA and listed in Table 4. It is clear from Table 4 that cubic model is able to capture more than 95% of the variance of the responses, indicating that the model is of high fidelity. The Adjusted $R^2$ is more reasonable in evaluating model significance because it considers the effect of factor count in the model. The reduced model exhibits higher Adjusted $R^2$ than the full model by removing insignificant terms.

It was found that the $\rho_p$ related effects – including main effect, curvature effect and interaction effect – are not significant to all the responses. For other factors with insignificant main effect, significant interaction effects related to these factors were detected in the full cubic model. The contribution of each factor was quantified and the top ten effects for each component were shown in Pareto chart.

It is clear from Figure 9 that the main effect of pump camber peak ($y_p^P$) dominates the effects to all the hydrodynamic performance. The contribution rates of $y_p^P$ are 44.2%, 53% and 25.2% for $TR_0$, $C_0$ and $\eta_{\text{max}}$, respectively, indicating a strong linear relationship between $y_p^P$ and torque converter performance. The DOE results suggest that $y_p^P$ is the parameter to alter when the designer wants to tune the torque converter performance by modifying pump.

The main effect plot of $y_p^P$ in Figure 10 reveals strong linear relationship between $y_p^P$ and responses. $C_0$ and $\eta_{\text{max}}$ exhibits positive trend regarding $y_p^P$, while $TR_0$ decreases with an increasing $y_p^P$.

Figure 11 shows that the critical turbine blade parameters for the hydrodynamic performance are $x_p^T$, $y_p^T$ and $\phi^T$. Quadratic effects were also found to be important, especially for $\eta_{\text{max}}$, of which the most influential effect is the quadratic effect of turbine blade leaning angle ($\phi^T)^2$.

The relationship between $\phi^T$ and peak efficiency is shown in Figure 12. Strong quadratic effect was observed. Peak efficiency increases firstly with an increasing $\phi^T$. However, it begins to decrease after it reaches the turning point, which is approximately 30° for the base torque converter configuration.

The most influential stator blade parameter is $y_p^S$, and its quadratic effect ($y_p^S)^2$ dominates the variation of $\eta_{\text{max}}$ with a contribution rate of 33.2%, see Figure 13. It is worth noting that strong interaction effect was also found between $x_p^S$ and $y_p^S$ with regard to $TR_0$, with a contribution rate as high as 19%.

Figure 14 depicts the response surface and interaction effect between $x_p^S$ and $y_p^S$ in terms of $TR_0$. The

Figure 9. Top 10 effects rated by contribution rate (%) for pump variables with regard to (a) $TR_0$, (b) $C_0$ and (c) $\eta_{\text{max}}$. 
Figure 10. The main effect plot for $y_p^P$.

Figure 11. Top 10 effects rated by contribution rate (%) for turbine variables with regard to (a) $TR_0$, (b) $C_0$ and (c) $\eta_{max}$.

Figure 12. The quadratic relationship between $\phi^T$ and $\eta_{max}$.

Prior to optimization, the parameters were categorized into three groups: the insignificant design variable (IV), the effective design variable (EV) and the primary design variable (PV). If all the effects – including main effect, curvature effect and interaction effect – regarding one factor are insignificant to the model under a threshold $p$-value of 0.05, then it is an insignificant factor. If the model can maintain an adjusted $R^2$ of more than 0.9 by removing one factor and all related effects containing that factor, then the factor is regarded as effective design variable. The rest of the factors fall into the primary design variable group. When it comes to optimization, the designer should first consider the primary design variables, as their effects contribute at least 90% of the variance to the response. The parameters in the effective variable group can be considered when the performance requirements were not satisfied after the primary design variables optimization. The designer could exclude insignificant variables in the optimization process as the variation of these factors does not affect the performance at a statistically significant level. The categorization results for the base model are listed in Table 5.

response surface is highly twisted, indicating strong interaction effect. From the interaction effect plot, one can see that when $y_p^S$ is at its low level, no significant effect is observed between $x_p^S$ and $TR_0$. However, if $y_p^S$ is at its high, strong negative relationship is found between $x_p^S$ and $TR_0$. 

Prior to optimization, the parameters were categorized into three groups: the insignificant design variable (IV), the effective design variable (EV) and the primary design variable (PV). If all the effects – including main effect, curvature effect and interaction effect – regarding one factor are insignificant to the model under a threshold $p$-value of 0.05, then it is an insignificant factor. If the model can maintain an adjusted $R^2$ of more than 0.9 by removing one factor and all related effects containing that factor, then the factor is regarded as effective design variable. The rest of the factors fall into the primary design variable group. When it comes to optimization, the designer should first consider the primary design variables, as their effects contribute at least 90% of the variance to the response. The parameters in the effective variable group can be considered when the performance requirements were not satisfied after the primary design variables optimization. The designer could exclude insignificant variables in the optimization process as the variation of these factors does not affect the performance at a statistically significant level. The categorization results for the base model are listed in Table 5.
It was found that the curvature at the juncture for all three components had no significant effects on the performance and thus could be ignored during optimization process. Pump and turbine inlet wedge angle coefficients were found to have limited influence on hydrodynamic performance and thus fall into effective design variable group.

### 3.2. Optimization

Optimization was performed on the base model for higher output torque and better launching performance, thus $TR_0$ and $C_0$ were chosen as objectives corresponding to the requirement. The constraint $- \eta_{\text{max}} > 0.84$ was applied to make sure that the outcomes had better efficiency than the base model. The design variables were $X = PV_{C_0} \cup PV_{TR_0} \cup PV_{C_0}^T \cup PV_{TR_0}^T \cup PV_{C_0}^S \cup PV_{TR_0}^S$. Three insignificant factors $- \rho_{pP}^P, \rho_{pT}^T$ and $\rho_{pS}^S$ and two effective factors $- \tau_{iP}^P$ and $\tau_{iT}^T$ were removed from the design variable pool based on the categorization results in Table 5. The optimization problem can be formulated as

$$\max y = f(X) = (TR_0(X), C_0(X))^T$$

$$X = \{x_P^P, y_P^P, N_P^P, \phi_P^P, \gamma_P^P, \tau_0^P, x_T^T, y_T^T, N_T^T, \phi_T^T, \gamma_T^T, \tau_0^T, x_S^S, y_S^S, N_S^S, \phi_S^S, \gamma_S^S, \tau_0^S, \tau_i^S\}$$

S.T. $\eta_{\text{max}} > 0.84$

The upper and lower bounds for the variables were as listed in Table 3. NSGA-II was used as the optimization algorithm. 40 individual designs were evaluated in each generation and the optimization was done by 250 generation evolutions, which required a total of 10,000 function evaluations. The Pareto solutions determined in the DOE process were added in the initial population to expedite the optimization.
The results are shown in Figure 15. Within a total of 10,000 samples, 196 non-feasible solutions (solutions with peak efficiency less than 84% or failed blade shape evaluation) were detected and 345 Pareto solutions were determined. The optimization offers us a series of torque converter cascades from which we can select according to our practical engineering requirements. Two typical solutions were chosen from the Pareto-front. Solution No.1 was selected for buses as it was able to provide much higher efficiency. Solution No.2, which exhibited higher torque capacity, was chosen for construction machinery because it was able to match low-speed engines and transmit higher torque. The blade geometries for the selected solutions are shown in Figure 16.

The design variables and performance for the selected two solutions derived from optimization are listed in Table 6. According to the steady-state CFD simulation
Table 6. Optimization results for the selected two solutions and base model.

| Model | Wheel | $\tau_0$ | $\varphi$ (°) | $x_p$ | $y_p$ | $y_\gamma$ (°) | $N$ | Performance |
|-------|-------|----------|-------------|-------|-------|---------------|-----|-------------|
| Base  | Pump  | 1.82     | 30.7        | 0.592 | 0.095 | 47.18         | 22  | $TR_0$ 2.45 |
|       | Turbine| 1.53     | 29.2        | 0.291 | 0.35  | 0.15          | 24  | $C_0$ 2.54  |
|       | Stator | 1.22     | -37.9       | 0.36  | 0.199 | 0.04          | 20  | $\eta_{max}$ 0.84 |
| No.1  | Pump  | 1.34     | 1.4         | 0.491 | 0.072 | -3.14         | 28  | $TR_0$ 2.69  |
|       | Turbine| 1.27     | 8.5         | 0.284 | 0.325 | 6.48          | 19  | $C_0$ 3.76  |
|       | Stator | 1.24     | -40.1       | 0.451 | 0.217 | -25.4         | 14  | $\eta_{max}$ 0.905 |
| No.2  | Pump  | 2.21     | 3.6         | 0.612 | 0.232 | 18.34         | 29  | $TR_0$ 2.54  |
|       | Turbine| 1.64     | 25.4        | 0.351 | 0.402 | 32.58         | 25  | $C_0$ 4.67  |
|       | Stator | 1.45     | -17.3       | 0.434 | 0.316 | -14.27        | 22  | $\eta_{max}$ 0.861 |

Figure 17. The velocity distribution at design condition in (a) solution No.1 and (b) base model.

Figure 18. The eddy viscosity distribution in the pump domain at design condition in (a) solution No.1 and (b) base model.

The reverse flow increases the flow loss, leading to lower efficiency. The velocity vector distribution plot (Figure 17) shows that at design condition, the flow in solution No.1 is much smoother than the flow in the base model. A large reverse flow region can be found on the pump blade suction side near the outlet in the base model, while no pronounced reverse flows can be detected in No.1 flow field. The eddy viscosity distribution in the pump domain reveals the significant difference in terms of turbulence between base model and No.1 model (Figure 18). The eddy viscosity increases extensively around the reverse flow region in the base model, while the eddy viscosity in No.1 model is much smoother and smaller, resulting in higher efficiency.

The velocity and pressure distributions could explain the flow mechanism of capacity increase for solution No.2 at stall. It can be found that No.2 has a more twisted and longer pump blade, which can transmit more power to the fluid, consequently leading to higher flow velocity and flow rate (Figure 19(a)). Torque capacity is directly related to flow rate, thus No.2 model exhibits higher
3.3. Validation

Full 3D transient CFD models of all three torque converters were built to calculate the hydrodynamic performance more accurately. The selected two torque converters were fabricated and tested, and the results are shown in Table 7.

It is found that the periodic steady-state CFD simulations used in the optimization process deviate within 8% for $TR_0$ and $\eta_{\max}$, while the error increased abruptly in terms of $C_0$ for higher capacity torque converters, with a maximum prediction error of 12.5%. The huge $C_0$ prediction error is found to be a consequence of cavitation. The fluid velocity and pressure differential between blade pressure and suction surface increase with an increasing capacity factor, leading to lower local pressure and higher risk for cavitation. The full 3D transient CFD model is able to increase the fidelity by considering transient and cavitation effects. As a result, the transient CFD model reduced the prediction error to within $\pm$ 4% for all hydrodynamic performance characteristics.

The base torque converter is a low capacity torque converter with very limited attached sheet cavitation at stator nose, as shown in Figure 20(a), so neglecting cavitation would not lead to a huge prediction error. For optimum solution No.1 whose capacity was increased by 44%, the cavitation region expanded along the stator suction surface as shown in Figure 20(b). For solution No. 2, torque converter capacity was further increased by 76%, the cavitation region grew further downstream on suction side and covered the entire stator nose, as shown in Figure 20(c). The cavitation bubble also detached from stator nose and traveled downstream, leading to performance degradation in both capacity and torque ratio. The cavitation bubble is able to block the main stream, resulting in severe flow rate reduction, i.e. capacity degradation.

Thus, it is necessary to evaluate the design with cavitation modeling before moving on to manufacturing, especially for high capacity torque converters.

The test results suggested that for solution No.1, the hydrodynamic performance had been improved by 6.8%, 44.2% and 6.5% in terms of $TR_0$, $C_0$ and $\eta_{\max}$, respectively. Whereas for solution No.2, huge capacity improvement (72.9%) was achieved, and performance gain in terms of $TR_0$ and $\eta_{\max}$ were 2.6% and 1.2%, respectively.

### Table 7. Performance validation with transient CFD model and test data.

|       | $TR_0$ | $TR_0$-err | $C_0$ | $C_0$-err | $\eta_{\max}$ | $\eta_{\max}$-err |
|-------|--------|------------|------|-----------|--------------|------------------|
| Base  | Steady-state | 2.45 | 4.3% | 2.54 | 5.8% | 0.84 | 0.8% |
|       | Transient   | 2.44 | 3.8% | 2.45 | 2.1% | 0.843 | 1.2% |
|       | Test      | 2.35 | – | 2.4 | – | 0.833 | – |
| No.1  | Steady-state | 2.69 | 7.2% | 3.76 | 10.3% | 0.905 | 2.0% |
|       | Transient   | 2.48 | –1.2% | 3.34 | 3.8% | 0.895 | 0.9% |
|       | Test      | 2.51 | – | 3.46 | – | 0.887 | – |
| No.2  | Steady-state | 2.54 | 5.4% | 4.67 | 12.5% | 0.861 | 2.1% |
|       | Transient   | 2.36 | –2.1% | 4.31 | 3.9% | 0.853 | 1.2% |
|       | Test      | 2.41 | – | 4.15 | – | 0.843 | – |

4. Conclusion

This research is devoted to the application of a CFD-based optimization approach to torque converter cascade design, with particular focus on parameterization method and optimization procedure. A Bezier-curve based parameterization method was utilized to represent blade shape. A blade shape evaluation method was proposed based on the manufacturability constraints to expedite the optimization process by skipping unnecessary calculations. A low-fidelity CFD model was used in the parameter study and optimization processes due to its low computing time requirement. Then, a high-fidelity CFD model was employed to evaluate the final solutions.
The DOE results suggest that main effect of pump camber peak dominates the effect on hydrodynamic performance, while turbine blade leaning angle affects the peak efficiency in a quadratic manner. The curvature at the juncture had little effects on the hydrodynamic performance and thus can be removed from the design variable pool to simplify the optimization. Primary parameters for all three components were determined and it was found that pump and turbine inlet wedge angle coefficient had limited effect on hydrodynamic performance.

The comparison between low-fidelity and high-fidelity CFD models exhibited pronounced deviation, especially in terms of capacity factor due to heavy cavitation. The periodic steady-state simulation used in optimization search yielded a maximum of 12.5% deviation, while the transient full 3D model considering cavitation was able to limit the prediction error to within ±4%. The combination of low-fidelity and high-fidelity CFD model ensures the efficiency and accuracy of the design procedure.

The proposed torque converter design approach is able to expand the design space by using a flexible blade parameterization and improve the design accuracy by implementing a CFD-O technique. Two optimum solutions were fabricated and tested. The results showed significant performance improvement compared to the base model and thus validated the CFD-O design method. The proposed torque converter design approach neglects the influence of torus design as well as the thickness distribution to the hydrodynamic performance. Therefore, future work could focus on a comprehensive parameter study and optimization method considering more degrees of freedom.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

**Funding**

This work was supported by National Natural Science Foundation of China: [grant numbers 51475041 and 51805027]; Vehicular Transmission Key Laboratory Fund: [grant number 61422130405]; Beijing Institute of Technology Research Fund Program for Young Scholars: [grant number 3030011181804].

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