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Multi-stakeholder service life design for rail level crossings

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ABSTRACT: Improvement in rail asset safety, comfortability and serviceability is gaining importance. This requires effective service life management by incorporating multi-stakeholder desires in the early design stage. Typical stakeholders are asset owners, train users and maintenance service providers. To allow for this change, the traditional single-sided engineering mechanics track design approach requires a shift towards an integrative design approach that best fits for common purpose while assuring continuous rail asset performance. Within the current paper, a multi-objective simulation-based optimization methodology that combines finite element modeling with preference function modeling is proposed to integrate multi-stakeholder preferences into the service life design. The applicability of the methodology is demonstrated in a design case for level crossings. It is shown that integrating specific stakeholders' preferences will substantially influence the optimal track design configuration, allowing the level crossing design to be managed focusing on best fit for common purpose rather than on mechanical behavior only.

1 INTRODUCTION

Transition zones in a railway network occur at changes in track form and or substructure properties. Examples can be found where a track transits from the open track (normally of the ballast type) to a slab track section to cross a roadway or waterway through supporting structures such as bridges and level crossings. The variation in track form causes a sudden change in track support stiffness, which gives rise to additional dynamic forces when vehicles pass by, associated with a change in elevation of the wheels. This, over a number of loading cycles, leads to the development of differential settlement between the (settlement-free) supporting structures and connecting track, which further increases loads and accelerates track degradation through successive deterioration of track geometry and components (Le Pen et al., 2014).

A typical design guiding principle for mitigating the transition problems is to reduce the dynamic amplification by smoothing stiffness variations along the track. This can be achieved by modifying railpad stiffness, varying sleeper sizes, and installing under sleeper pads at transitions (Indraratna et al., 2019). Amongst these measures, incorporating elastic elements (e.g., the railpads) with different properties can be considered an efficient means to vary track vertical stiffness and dampen vibrations and noise (Sol-Sánchez et al., 2015). Besides, sleepers act as supporting elements to distribute vehicle loads on the track. The design parameters such as spacing and size are also relevant to the local track dynamic behavior. For instance, a reduction in sleeper distances causes an increase in track (vertical) support stiffness, which however also implies more construction costs. As Ortega et al. (2021) reported, the separation of 1 m per spacing results in a 40% cost reduction per km compared to the standard sleeper spacing (0.6 m).

Parametric variations can effectively provide a design solution that allows for a homogeneous distribution of stiffness throughout the track, reducing the dynamic impact in the vehicle-track system and improving long-term track performance. This further reduces the associated maintenance efforts/costs, relevant to the management goals of maintenance service providers. Besides, as

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system dynamics are interactive between the vehicles and track, the level of track dynamic amplification also influences the vehicle system responses, e.g., carbody accelerations, which relate closely to the driving comfort of passengers and hence the level of service.

The above impact of variations in track design reflects multi-stakeholder desires. It demonstrates that the railway track design requires an integrative approach incorporating both rail asset feasibility (technics) and stakeholder desirability (e.g., affordability, serviceability). However, the traditional ways of designing the transitions (or the railway track in general) mainly focused on meeting one single technical objective. The mitigation measures for the transitions are mainly developed based on mechanical responses such as wheel-rail contact forces without considering related social needs.

The current study proposes a novel way of integrating hard engineering and soft social aspects to model design problems for railway track structures. Since stakeholder objectives might be conflicting (where no single design solution exists that simultaneously satisfy all), integrating multi-perspectives to evaluate track design alternatives requires optimization techniques to balance stakeholders' preferences and actual rail structural performance. For this purpose, a preference-based optimization tool is combined with a finite element (FE)-based model to capture a wider variety of design aspects. The former translates vague societal needs into crisp engineering design variable values. The FE model characterizes the track dynamic behavior under moving vehicles and serves as a basis for parametric optimization.

2 METHODOLOGY

2.1 *Overview - problem definition*

The relationship between track input parameters and dynamic responses can be defined by

$$\mathbf{y} = g\ (\mathbf{x}) \tag{1}$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ is a vector containing a list of track parameters defined in n-dimensional space, e.g., railpad stiffness, sleeper spacing. $\mathbf{y} = (y_1, y_2, \ldots, y_k)$ is the vector collecting k responses of interest. Eq. (1) is defined by a FE model, which is introduced in Section 2.2.

Three stakeholder groups are of high relevance in railway service life management, i.e., asset owners, train users, and maintenance service providers. Their interests can be reflected in investment cost, riding comfort, and long-term track performance, respectively (see Table 1).

Table 1. Objectives and performance measures.

Objectives	Performance measures	Unit
Minimize initial investment	C_{cap} - investment cost	€
Maximize riding comfort	A_{max} - max-to-min of carbody acceleration	m/s^2
Minimize expected long-term degradation	E_{max} - max. differential energy dissipation	N·m

Specifically, 1) the sleeper spacing and number of strengthened sleepers in a transition can influence the investment cost. 2) The riding comfort is quantified by *max-to-min difference of carbody accelerations* induced when a vehicle passes through a transition. The lower the carbody accelerations, the higher level of service is expected. 3) The long-term degradation mainly concerns the damage to the ballast layer, as it is the main driver causing track geometry degradation in the transitions. This can be directly related to the mechanical energy dissipated in the ballast layer. The *maximum differential energy dissipation* between adjacent sleepers is selected here as an indicator to assess the sensitivity of a track design to the expected damage (Sadri et al., 2019). The higher the energy dissipated into the ballast layer, the stronger the degradation can be expected. Therefore, reducing the amount of dissipated energy represents an important aim for damage reduction in overall track geometry condition and savings in maintenance efforts/costs.

The objective C_{cap} is evaluated through an explicit function, which is elaborated in Section 3. A_{max} and E_{max} are quantities generated from numerical simulations, where an FE-based model is developed (Section 2.2) to model the coupling dynamics between the vehicle and track.

2.2 *Modeling of vehicle-track dynamics*

A numerical model is developed to simulate vertical dynamic interaction between the railway track and moving vehicle, which is parametric for optimization purposes. As shown in Figure 1, the vehicle is represented by a multi-body system consisting of a carbody, a bogie, and a wheel, which are connected through suspension systems. The vehicle travels at a constant speed on a ballast-slab transition. The load from the vehicle is assumed to be symmetrically distributed, and consequently, half of the track is studied in this work.

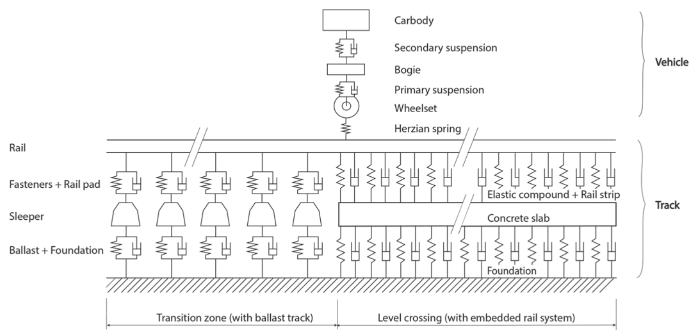

Figure 1. Schematics for a vehicle and a ballast-slab transition.

The track structure is formulated by FEM: the ballast track (left) is represented by a two-layer discretely supported model, and the slab track (right) is continuously supported according to system features of the embedded rail system (ERS). Various design options are available for slab track structures. We consider ERS in this work as it is an innovative track design solution and has been increasingly employed in discrete railway assets such as bridges and level crossings. For details of the ERS features, the reader is referred to Yang et al. (2021).

In the model, the rail and concrete slab are meshed with Euler-Bernoulli beam elements. The supporting components in the ballast track consist of railpads represented by Kelvin-Voight (KV) elements, sleepers as masses, and underlying ballast and foundation layer modelled collectively as the KV elements. Similar to the railpads in the ballast track, elastic compound and rail strip in ERS are placed underneath the rail to provide track elasticity and constrain the vertical rail deflection, which is also modelled by the KV elements, as proposed in Yang et al. (2021).

The vehicle-track interaction problem is solved by integrating the two subsystems into a global system, where the individual system matrices are coupled to formulate global ones, and the global equations of motion (EOM) can be expressed as

$$\mathbf{M}_g\ddot{\mathbf{U}}_g + \mathbf{C}_g\dot{\mathbf{U}}_g + \mathbf{K}_g\mathbf{U}_g = \mathbf{F}_g \tag{2}$$

where $\mathbf{M}_g$, $\mathbf{C}_g$ and $\mathbf{K}_g$ denote, respectively, the mass, damping, and stiffness matrices of the global system. $\mathbf{U}_g$,$\dot{\mathbf{U}}_g$ and $\ddot{\mathbf{U}}_g$ are the displacement, velocity, and acceleration vectors of the global system, respectively. $\mathbf{F}_g$ is the global force vector.

The track model is developed in COMSOL, where the system matrices are formulated and exported to MATLAB. The vehicle system matrices are established in MATLAB, which are then coupled with the exported track matrices to formulate the global ones, as written in Eq. (2). The global EOM is solved in the time domain using the Newmark integration method, which is implemented in MATLAB. This co-simulation methodology of connecting COMSOL and MATLAB to solve vehicle-structure dynamics was first developed and validated with a beam case by Shang et al. (2022) and extended to a railway structure by Shang et al. (2023). The reader is referred to these works for extensive descriptions of the coupling method.

2.3 *Preference based design optimization*

Multi-objective design optimization (MODO) applies to decisions that need to be taken in the presence of trade-offs between several objectives. This applies to all types of design scenarios, including the railway track design. Various methods have been devised to solve MODO problems, which can be categorized depending on how the designer articulates the preferences, i.e., a priori and a posteriori articulation of preferences. *A priori* articulation indicates that the relative importance of the objective functions is specified before running the optimization. In cases where no a priori information is available, it is adequate to map all potential solutions and allow the designer to make a decision afterward. Such methods are referred to as *a posteriori* methods.

A priori methods are reflected by parameters such as weights and aggregation scores (Zhilyaev et al., 2022; van Heukelum et al., 2022). The weighted min-max (or goal attainment) approach is a common solution technique in a priori methods. The basic idea is that the designer specifies a target value (i.e., the goal) for each objective, and the 'min-max' seeks to find a solution that minimizes the maximum deviation between the target values for the objectives and values of a candidate solution. When it is applied in the preference-based decision-making domain, all the solutions are mapped by preference scores on a 0-100 scale, and the value of 100 implies the goal. This solution mapping essentially translates the stakeholder preference into deviation from the goal in relative terms, and the minimization of the largest deviation can be formalized as

$$\underset{\mathbf{x}}{minimize} \quad U = \max_{i}\{w_i \times [100 - P_i(g_i(\mathbf{x}))]\} \tag{3}$$

where $g_i(\mathbf{x})$ represents the value of i^{th} (i = 1, 2, 3) objective (see Table 1) given a specific design configuration $\mathbf{x}.P_i\,(\cdot)$ is the preference function corresponding to i^{th} objective. It translates $g_i(\mathbf{x})$ to a preference measurement, where stakeholder preference information is encoded in the function and used to rank design solutions. w_i is the weight associated to i^{th} objective.

In each single run, the 'min-max' approach produces a single best solution, representing the best compromise among stakeholders. To provide more flexibility in the decision making process, a posteriori articulation is integrated as an alternative in the proposed methodology to solve the MODO problem. Techniques based on genetic algorithms (GA) seem suitable for solving MODO as they can simultaneously handle a set of potential solutions (or a population). This allows the designer to find several members of the Pareto set in a single run of the algorithm (Chang, 2014). The GA-based approaches have extensive applications in railway mechanics, such as the design of vehicle suspensions (Alkhatib et al., 2004), switches and crossings (Pålsson & Nielsen, 2012), and a ballast-slab transition (Aggestam & Nielsen, 2019).

One of the most popular GA-based approaches for MODO is the Nondominated Sorting Genetic Algorithm II (NSGA-II) developed by Deb et al. (2002). The process includes the creation of the initial population and design iterations. Initial individuals are randomly created, and function evaluations are performed for each individual, which is then sorted based on two attributes: nondomination rank and crowding distance. The nondomination rank of an individual is assigned by comparing its function value with the rest. The lower rank (higher fitness) is preferred between two solutions with different ranks. Further, the crowding distances apply when the solutions are in the same rank, and the solution in a less crowded area is preferred. The computation of the two entities guides the selection process at each iteration toward a uniformly spread-out Pareto front (Chang, 2014). Further details of the sorting process are referred to Deb et al. (2002).

2.4 *The Kriging metamodel*

Applying optimization algorithms in railway mechanics is in general a computationally demanding task. Simulating railway mechanics often requires advanced computational methods, e.g., FEM and discrete element method. The evaluation of these models can be time-consuming and even more challenging when vehicle-track interaction is considered (as is the general case in transition-related works). To keep the computational cost affordable, metamodeling techniques are integrated into the current methodology, which can provide accurate approximations to the responses of the FE model (see Section 2.2) at reduced computational time.

Metamodeling (also known as surrogate modeling) is frequently used across engineering disciplines in combination with physical experiments or expensive simulation models. Due to the computational efficiency (than the original model), it often supports engineering tasks that require the design space exploration, such as design optimization, model calibration and reliability analysis.

The effectiveness of using metamodels is interconnected with the problem types and modeling conditions (e.g., dimensionality, (non)linearity, sample size). Kianifar & Campean (2020) systematically compared the performance of several metamodeling options in relation to the well-defined problem categories, where the Kriging model with Matérn 5/2 correlation function shows competing performance among the candidates in terms of accuracy and robustness. Therefore, we choose the Kriging model in this work to approximate Eq. (1), which can be expressed as

$$\hat{g}\ (\mathbf{x}) = \mathbf{f}^{\mathbf{T}}\ (\mathbf{x})\ \beta + Z\ (\mathbf{x}) \tag{4}$$

where $\hat{g}\ (\mathbf{x})$ is the approximation of $g\ (\mathbf{x})$ predicted by the Kriging. $\mathbf{f}^{\mathbf{T}}\ (\mathbf{x})\ \beta$ is the mean value of $\hat{g}\ (\mathbf{x})$, including q arbitrary functions $\{f_j;\ j\ =\ 1,\ \ldots,\ q\}$ and the corresponding coefficients $\{\beta_j;\ j\ =\ 1,\ \ldots,\ q\}$. It represents the global characteristics (the trend) of the model. Z ($\mathbf{x}$) captures the local deviations by a Gaussian process with expectation being zero and variance being σ^2.

For a single objective, when training samples $\mathbf{x} = \{\mathbf{x}_1,\ \mathbf{x}_2,\ \ldots,\ \mathbf{x}_m\}^T$ are determined, the corresponding output $\mathbf{y} = \{y_1,\ y_2,\ \ldots,\ y_m\}^{\mathrm{T}}$ can be obtained by querying the FE model at $\mathbf{X}$. This forms a training set $\Phi = \{(\mathbf{x}_i,\ y_i)|i = 1,\ \ldots, m\}$, and the covariance of $Z\ (\mathbf{x})$ can be given by

$$\mathrm{cov}\ \left[Z\ (\mathbf{x}_i),\ Z\ \left(\mathbf{x}_j\right)\right] = \sigma^2 R\ \left(\mathbf{x}_i, \mathbf{x}_j\right) \tag{5}$$

where R ($\mathbf{X}_i$, $\mathbf{X}_j$) is the correlation function for any pair of ($\mathbf{X}_i$, $\mathbf{X}_j$). The Matérn 5/2 correlation function is used given its accuracy and robustness as evaluated by Kianifar & Campean (2020).

3 ILLUSTRATIVE EXAMPLE: A RAIL LEVEL CROSSING

3.1 *Optimization problem formulation*

A level crossing design case is selected to demonstrate the application of the proposed methodology. A ballast-slab transition is often presented in a level crossing, where the ERS design (with concrete slabs installed to replace the ballast layer) is applied for crossing traffic. This poses an abrupt variation in track support stiffness since the connecting section is of the ballast type. The current optimization problem is therefore formulated to achieve a smooth stiffness transition between the connecting ballast track and ERS-based level crossing.

The design variables are listed in Table 2, which are collected in a design vector $\mathbf{X}$ ($\mathbf{X}$ = [x_s, x_n, x_{r1},x_{r2}, x_{r3}, x_l]). The variable x_l is specific to ERS design, while the others are related to the ballast track. The rail strips in ERS are elastic components underneath the rails, similar to the railpads in the ballast track. Two types of rail strips with predefined stiffness properties have been developed for ERS. The current practice in the Netherlands utilizes type I strip, and the effect of applying (softer) type II strip on the mechanical behavior of level crossings is under investigation. It is also worth mentioning that the variables x_s and x_l are treated as discrete values to align the optimization setting with the FE discretization. The value implies the number of 0.05m-long finite elements. The lower bound of x_s means 0.5 m, and the upper bound is 0.7 m. This range is considered reasonable and can maintain structural integrity, according to Ortega et al. (2021). x_l has a lower bound of 0 and upper bound of 6 m, implying that a 6-m level crossing is considered in the example.

The track parameters in the FE model are defined according to a typical Dutch level crossing design. The vehicle parameters refer to VIRM trains, which are double-deck trains operated by Dutch Railways. For details of the parameter setting, the reader is referred to Shang et al. (2023).

Table 2. Definition of design variables.

Variables	Unit	Range of definition	Related objectives
Sleeper spacing (x_s)	-	$x_s \in Z : x_s \in [10, 14]$	A_{max}, C_{cap}, E_{max}
Number of strengthened sleepers (x_n)	-	$x_n \in Z : x_n \in [0, 15]$	A_{max}, C_{cap}, E_{max}
Railpad stiffness (x_{ri}, i = 1, 2, 3)	MN/m	$x_{ri} \in R : x_{ri} \in [50, 1000],\ i = 1 \cdots 3$	A_{max}, E_{max}
Length of type II rail strip (x_l)	-	$x_l \in Z : x_l \in [0, 120]$	A_{max}, E_{max}

Three objectives (see Table 1 and 2) are considered in the optimization. Two Kriging metamodels are established to approximate E_{max} and A_{max}, respectively. Initially, 2000 points of **x** are generated based on Latin Hypercube sampling. The FE model is queried at these input locations to generate the quantities of E_{max} and A_{max}. The input-output formulates a dataset further split into training, validation, and test sets. The Kriging parameters are tuned based on the leave-one-out (LOO) cross-validation (CV) approach using the training and validation data. The model performance is evaluated on the test set using relative training error, which yields 2% and 1% for the metamodels of predicting E_{max} and A_{max}, respectively.

The objective C_{cap} is calculated depending on x_s and x_n. 1) x_s is varied within a 5-m section adjacent to the level crossing. Ortega et al. (2021) analyzed the effect of sleeper spacing (x_s) on construction cost savings. A brief resume of cost reduction in spacing alternatives was reported compared with the standard spacing (0.6 m). This work utilizes this cost relation, where the total cost of placing sleepers with the standard spacing is assumed as €3000, and the costs for other spacing alternatives are calculated based on the cost ratio provided by Ortega et al. (2021). 2) x_n concerns the number of strengthened sleepers in the transition. It is assumed that the cost ratio between the strengthened and normal type is 1.5 and the unit cost of using the normal sleeper type in the transition region is €400.

3.2 *Results and discussion*

Single-objective optimization problems are firstly solved, and the results are presented in Table 3. The optimum produced from Alt. 1-3 represents the preferred track design solution for maintenance service providers, train users, and asset owners, respectively. The maximization problems in Alt. 4-6 are solved to gather extremes for each objective and facilitate the association of a preference function to each objective in the following multi-objective problem formulation.

Table 3. Design solutions and corresponding objective values from single-objective optimization. Optimal values are highlighted for each problem.

Design alternatives	Design solutions	Objective values		
	x=[x_s, x_n, x_{r1},x_{r2}, x_{r3}, x_l]	$E_{max}(N)$	A_{max}(m/s^2)	C_{cap}(€)
Alt. 1: E_{max} minimization	x=[13,6,139,179,50,30]	0.1107	0.2300	9967.7
Alt. 2: A_{max} minimization	x=[10,3,74,50,50,0]	0.1814	0.2148	10013
Alt. 3: C_{cap} minimization	x=[14,0,78,78,0]	0.2836	0.2529	8562.2
Alt. 4: E_{max} maximization	x=[14,0,885,50,1000,41]	1.3880	0.2332	8562.2
Alt. 5: A_{max} maximization	x=[14,4,50,593,792,84]	0.6909	0.2570	9362.2
Alt. 6: C_{cap} maximization	x=[10,15,78,78,78,0]	0.2160	0.2136	12413

The optimization of C_{cap} depends on variable x_s and x_n only (as highlighted in Design solutions to Alt. 3&6), and the remaining variables are fixed as default values. It can be observed that C_{cap} is conflicting with the other objectives: the design with larger sleeper spacing and 'zero' use of strengthened sleepers is preferable from a cost perspective; however, it does not help reduce expected damage in the ballast (E_{max}) and maintain the level of train service (A_{max}).

By comparing the solutions from Alt. 1-2 and Alt. 4-5, the first observation is that softer railpads (x_{ri}, i = 1, 2, 3) are recommended to reduce the dynamic impact in the vehicle-track system. In Alt. 1, the optimum of x_{r3} is far less than those for x_{r1} and x_{r2}. x_{r3} refers to the stiffness of the railpad adjacent to the crossing, and the optimum is linked to x_l. x_l = 30 means a 1.5m-long type II (softer) strip is recommended in connection with a soft railpad (x_{r3}) in the ballast track. This allows for a homogeneous distribution of track support stiffness. Hence, a lower effect of load transmitted to the ballast layer can be expected (i.e., reduced E_{max}). It also explains the optimal solution in Alt. 4, where a contradicting outcome is produced. Compared to Alt. 1, Alt. 2 suggests not using the softer strip in ERS in order to minimize A_{max}. The reason could be that E_{max} focuses on the dynamics in track underlayers while A_{max} relates to the upper vehicle dynamics.

The objective values in Table 3 show that by minimizing C_{cap} (Alt. 3), E_{max} and A_{max} will deviate from their minimum; however, E_{max} can be minimized without degrading A_{max} too much (Alt. 1). This can be explained by the interactive dynamics between the vehicle and track structure, i.e., the objectives E_{max} and A_{max} are correlated. It is also worth mentioning that the objectives considered depend on different design variables: C_{cap} is influenced by x_s and x_n only, while the others depend on the entire variable set. Therefore, the competing nature of these objectives can be observed but optimizing one does not necessarily lead to the opposite extremes of the others. Still, the MODO formulation is required as trade-offs are presented between the objectives.

In the MODO, a linear preference function is assigned for each objective. The max and min of each objective are used to construct a reasonable range for associating a preference function to an objective. For example, as shown in Figure 2 (a), for maintenance service provides, the preference for E_{max} of 0.1 equals 100, representing the desired level, and the preference for E_{max} of 1.4 equals 0, which is the worst scenario that should be avoided.

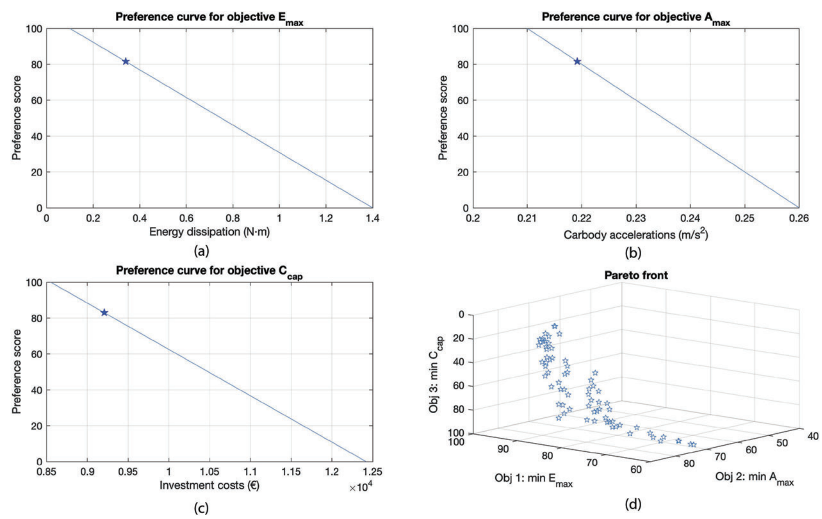

Figure 2. MODO outcomes: preference curve for objective (a) E_{max}, (b) A_{max}, and (c) C_{cap} including the optimum obtained from a priori min-max method; (d) Pareto front for three objectives from a posteriori GA-based approach.

The optimal objective values from the minmax method are also marked on the preference curves in Figure 2 (a)-(c), where equal weights are assigned. The objective scores are almost equal (~82), with E_{max} = 0.3398, A_{max} = 0.21982, and C_{cap} = 9207. Compared with the outcomes from single-objective problems (Table 3), it illustrates the rationale behind the goal attainment paradigm: the method seeks to find a balanced solution among the stakeholders. Besides, the solution is **X** = {11, 0, 89, 50, 50, 53}, showing that the soft railpads and strips (x_{ri}, x_l;i = 1,2,3) are recommended from both the single-objective and MODO problems at the junction between the level crossing and transition. However, compared with the single-objective problems, MODO formulation that integrates the stakeholders' preferences substantially influences the solution to sleeper parameters (x_s and x_n), since the variables have an actual influence on the objective C_{cap} and it is conflicting with the others.

The Pareto front generated from NSGA-II is presented in Figure 2 (d). It shows that none of the objective functions can be improved in value without degrading some of the other objective values. The solutions mapped on the front are equally good, allowing the designer to make a decision afterward.

4 CONCLUSIONS

Effective service life management of railway assets requires multi-stakeholder desires to be incorporated into the early design stage. This necessitates an integrative design approach that incorporates both rail asset feasibility and stakeholder desirability. For this purpose, the current work presents a novel way of integrating hard engineering and soft social aspects to model design problems for railway track structures. Three representative stakeholder groups and respective interests are defined in terms of railway mechanics, affordability, and serviceability. The perspectives are translated to preference measures, which are further used to formulate design optimization problems. Three techniques, namely, FEM, metamodeling, and preference-based modeling, are integrated into the optimization framework, which seeks to find optimal design configurations that balance stakeholder preferences and actual track performance in a reasonable computational effort. A level crossing design case is provided, where the obtained design solutions demonstrate relevance to stakeholder preferences and long-term track performance. It shows that the proposed methodology allows the track design to be managed focusing on best fit for common purpose rather than on mechanical behavior only. The case study is for demonstration purposes, and the design methodology is applicable to other railway asset types.

REFERENCES

Alkhatib, R., Jazar, G.N. & Golnaraghi, M.F. 2004. *Optimal design of passive linear suspension using genetic algorithm*. Journal of Sound and vibration, 275(3-5), pp.665–691.

Aggestam, E. & Nielsen, J.C. 2019. *Multi-objective optimisation of transition zones between slab track and ballasted track using a genetic algorithm*. Journal of Sound and Vibration, 446, pp.91–112.

Chang, K.H. 2014. *Design theory and methods using CAD/CAE: The computer aided engineering design series*. Academic Press.

Deb, K., Pratap, A., Agarwal, S. & Meyarivan, T.A.M.T. 2002. *A fast and elitist multiobjective genetic algorithm: NSGA-II*. IEEE transactions on evolutionary computation, 6(2),pp.182–197.

Indraratna, B., Sajjad, M.B., Ngo, T., Correia, A.G. & Kelly, R. 2019. *Improved performance of ballasted tracks at transition zones: A review of experimental and modelling approaches*. Transportation Geotechnics, 21, p.100260.

Kianifar, M.R. & Campean, F. 2020. *Performance evaluation of metamodelling methods for engineering problems: towards a practitioner guide*. Structural and Multidisciplinary Optimization, 61(1),pp.159–186.

Le Pen, L., Watson, G., Powrie, W., Yeo, G., Weston, P. & Roberts, C. 2014. *The behaviour of railway level crossings: Insights through field monitoring*. Transportation Geotechnics, 1(4),pp.201–213.

Ortega, R.S., Pombo, J., Ricci, S. & Miranda, M. 2021. *The importance of sleepers spacing in railways*. Construction and Building Materials, 300, p.124326.

Pålsson, B.A. & Nielsen, J.C. 2012. *Track gauge optimisation of railway switches using a genetic algorithm*. Vehicle system dynamics, 50(sup1), pp.365–387.

Sadri, M., Lu, T. & Steenbergen, M. 2019. *Railway track degradation: The contribution of a spatially variant support stiffness-Local variation*. Journal of Sound and Vibration, 455, pp.203–220.

Shang, Y., Nogal, M. & Wolfert, A.R.M. 2022. *A co-simulation solution for vehicle-track interaction dynamics problems*, in: The Fifth International Conference on Railway Technology: Research, Development and Maintenance, Elsevier, Montpellier, France.

Shang, Y., Nogal, M., Teixeira, R. & Wolfert, A.R.M. 2023. *Optimal design of rail level crossings and associated transition zones using adaptive surrogate-assisted optimization*. Engineering Structures, 282, p.115740.

Sol-Sánchez, M., Moreno-Navarro, F. & Rubio-Gámez, M.C. 2015. *The use of elastic elements in railway tracks: A state of the art review*. Construction and building materials, 75, pp.293–305.

van Heukelum, H.J., Binnekamp, R. & Wolfert, A.R.M. 2022. *Human preference and asset performance systems design integration*. Submitted to Structure and Infrastructure Engineering, under review.

Yang, Z., Zhang, P. & Wang, L. 2021. *Wheel-rail impact at an insulated rail joint in an embedded rail system*. Engineering Structures, 246, p.113026.

Zhilyaev, D., Binnekamp, R. & Wolfert, A.R.M. 2022. *Best Fit for Common Purpose: A Multi-Stakeholder Design Optimization Methodology for Construction Management*. Buildings 2022, 12, 527.