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A NOVEL FRAMEWORK TO EVALUATE THE PERFORMANCE OF RESPONSIVE KINETIC SHADING DEVICES

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ABSTRACT

Determining control parameters of kinetic shading devices introduces a dynamic problem to designers, which can best be tackled by computational tools. Yet, excessive computational cost inherits in reaching near optimum solutions led to exclusion of many design alternatives and weather conditions. Addressing the issue, the current study aims to explore the design space adequately and evaluate the performance of responsive-kinetic shading devices (RKSD) by proposing a novel framework. Current framework adopts a surrogate-based technique for multi-objective optimization of control parameters of a RKSD on randomly sampled daylight hours. To test the plausibility of any results obtained by the proposed framework, a controlled experiment is designed. Empirical evidences suggest RKSD outperforms the static one in daylighting and view performance metrics. However, considering indoor temperature no significant differences observed.

Keywords: responsive, kinetic, shading, daylight, temperature, view, simulation, surrogate, optimization

1. INTRODUCTION

Solar control has been historically a vital consideration in architectural design, since it is highly relevant with the concepts of energy and comfort. A proper control strategy by means of shading devices has dramatic influence on room temperature and natural lighting, accordingly, contributes to energy savings while providing comfort for the occupants [1]. Regulating the sunlight on the exterior of a facade, before solar beams enter the room and radiate its energy inside, is a much efficient strategy for sun control [1–3]. Conventionally, static shading devices are integrated to facades to perform this task. However, static devices fail in responding to fluctuating environmental and comfort demands. Lechner [4] put forward a critical question:

"Is it logical that a static system can respond to a dynamic problem?"

To tackle with the issue, responsive kinetic shading devices (RKSD), which forms the focus of the current research, were introduced. RKSD are defined as active shading systems. They consist of components with the ability to change themselves due to the change in the environment with help of kinetic movement in an automated manner. To be responsive, a shading device must possess moving parts, actuators, a control system, sensors and be programmed to respond in a certain way due to the sensor data. When designing a kinetic system, which accounts for change in time, the complexity of the design problem increases substantially. On the other hand, the developments in the computer technology along with new computational approaches, researchers gained the ability to deal with such complexity.

As a specific domain of computer aided design – performance integrated parametric design and performance optimization help making well-informed design decisions. However, information feedback in the design process comes at a price, which is computation time. Most of the simulation engines that generate such design information are computationally expensive. In the study of solar control with help of kinetic shading devices that respond to its environment, the problem of high computational times is even more significant. Because the determination of the values for the shading control parameters requires to be based on minor fractions of time.

A critical review of the literature on responsive kinetic shading devices revealed that most of the studies over-simplified the design problems due to the high levels of complexity and computational costs (i.e. [5–9]). Such simplifications may lead to deficiency in the exploration of the design space. For instance, El Sheikh & Gerber [10] and Sharaidin, Burry, & Salim [11] employed a meta-heuristic search method, namely genetic algorithm, towards exploration of design alternatives that have better daylight performance. Excessive number of simulations is required to converge to optimum design alternatives. Therefore, computational cost was extremely high as each population member for the given number of generations must be simulated in simulation-based optimization. In response, Wortmann et al. [12] argued that surrogate model based optimization outperforms simulation-based optimization in solving architectural design problems, both at computational cost and finding better solutions. For instance, Kazanasmaz et. al. [13] developed a predictive model by using artificial neural networks in order to predict daylight intensity for the office buildings in Izmir, Turkey. Parallel, Hu and Olbina [14] utilized surrogate models for predicting the influence interior split-blinds on illuminance levels and achieved very low prediction errors. Both works [13,14] focused only to daylight performance, by neglecting thermal and other visual comfort aspects such as view to the outside environment. In another instance, Skavara [15] implemented artificial neural networks for controlling the emergent behaviour of an exterior shading system that is driven by cellular automata for daylight performance. However, her focus was more on the training techniques of the neural networks, than the comfort and energy related influence of the responsive-kinetic shading device that she proposed.

Not only performance assessment using computational tools but also comparison between static and responsive-kinetic shading devices, have been considered by previous studies (i.e. [7,9,16,17]). In all cited studies, researchers concluded that kinetic shading devices outperform static ones. However, the static shading systems that they examined were not optimized for better performance. Additionally, in none of the works cited, view – one of the most important consideration in architectural design – has been considered as a performance objective, along with thermal and daylight objectives in the same problem. Finally, a single point in time was considered as a basis for comparison. Specifically, only a time-point in a year i.e. July at 11:00 a.m. was studied for comparison aims. Therefore, any results obtained by such limitations can reach to restricted conclusions.

To address the gap in the literature, the current study aims to explore the design space and evaluate the performance of RKSD adequately by proposing a novel framework. Current framework adopts a surrogate-based technique for multi-objective optimization of control parameters of a RKSD on randomly sampled daylight hours. To test the plausibility of any results obtained by the proposed framework, a controlled experiment is designed, which is detailed profoundly in Methodology section. Empirical evidences suggest RKSD outperforms the static one in daylighting and view performance metrics. However, considering indoor temperature no significant differences observed.

2. METHODOLOGY

The current research employed a quantitative approach for assessing the performance of shading devices. To achieve, a novel computational framework was proposed, Fig. 1. Next, the framework was tested in a comparative study between annually optimized-static and hourly optimized responsive-kinetic shading devices. It was hypothesized that responsive-kinetic shading devices would outperform optimized-static shading devices on the given performance metrics. To test the hypothesis, a controlled experiment was designed using the computational tools, which aims at measuring the influence of quantitative independent variables on selected performance metrics.

The current work considered three performance metrics. The first one is denoted by $|\Delta T|$ which is defined as the absolute value of the difference between the air temperature simulated inside the hypothetical box model and 23 °C threshold. The second

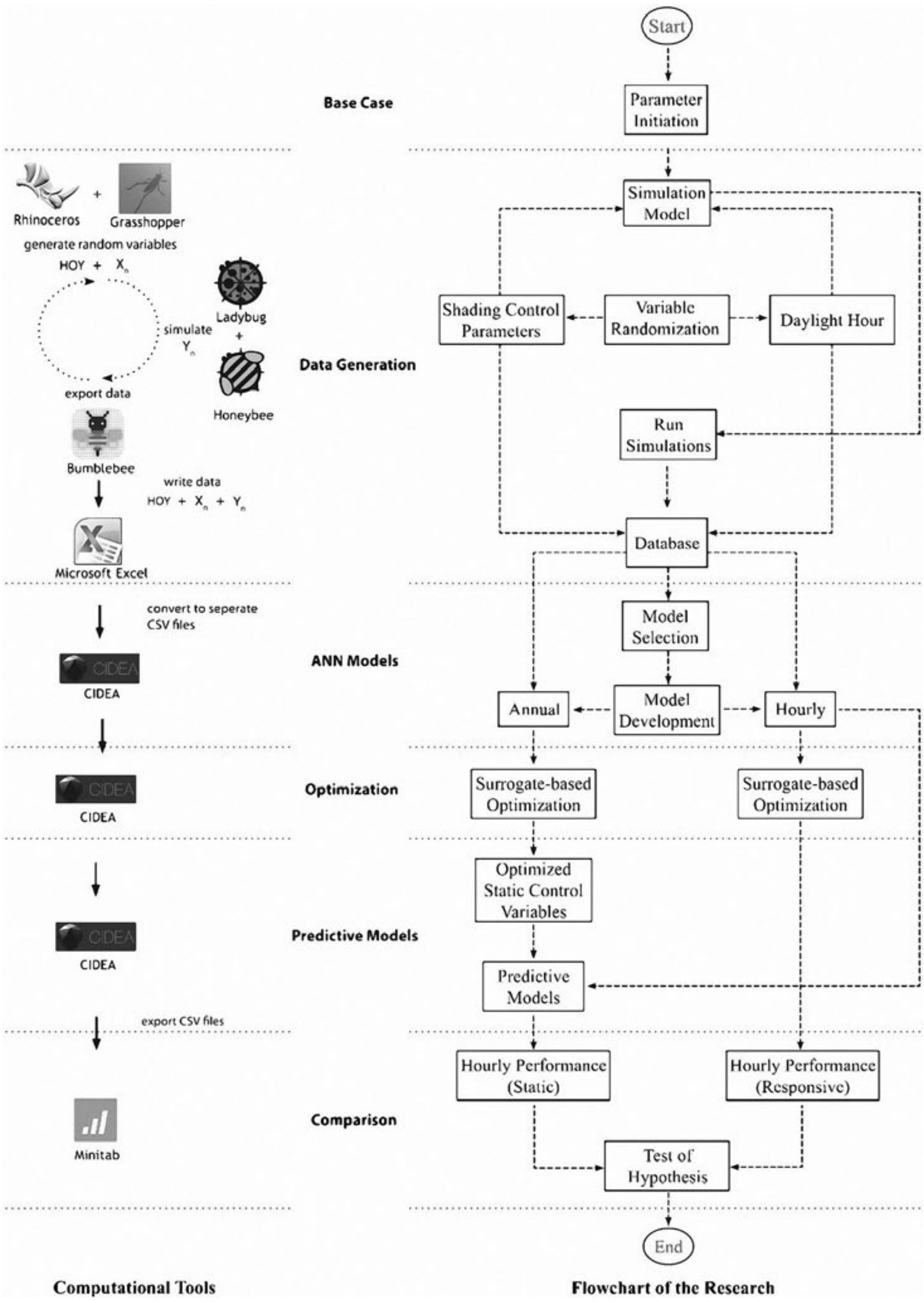

Fig.1.The computational tools used and the flow-chart of the experimental design

performance metric is denoted by $|\Delta lux|$ which is the absolute value of the difference between the average illuminance what was simulated inside the hypothetical box model and 500 lx thresholds. Finally, last performance metric is the average of the *View* percentage from a given point inside to the view frame at the outside

2.1. Box Model Properties

Within the content of experiment design, first, a test box was defined for the study of the exterior shading devices. At each of the shading device scenarios, parameters of this test box were kept constant. The dependent variables of annually-optimized and responsive kinetic shading systems on the base building were examined. The location of the Box-Model was Izmir, Turkey. Crucial to underline, to eliminate the influence of other confounding factors and thus measuring the sole impact of shading device on selected performance metrics; heat transfer was allowed only from the south-facing façade in the current experimental design. Furthermore, it was assumed that there were no internal

Table 1. Parameter Initiation of the Box-Model

Parameters		**Values**
Location		**Izmir /Turkey**
Dimensions	Width, m Depth, m Height, m	3 6 3
Reflectance	Floor,% Ceiling,% Walls,% Shading (exterior),%	30 80 50 40
U Values (heat transfer coefficient)	Walls (except South) Roof Floor Window, W/($m^2 \cdot$ K) South Wall, W/($m^2 \cdot$K)	Adiabatic Adiabatic Adiabatic 2.39 0.49
Internal Loads	Equipment, W/m^2 Infiltration Rate, (m^3/s)/m^2 Irradiance, W/m^2 People Density, ppl./m^2	 0.003 0 0
Window	Orientation Glazed Area, m^2 Window to Wall Ratio Window Construction	South 7.84 0.87 Double Pane with Low *E*
Glass Material	Type Visible Transmittance Refraction Index	Clear glass 0.79 1.52

heat loads. Table 1 demonstrates the initial parameters of the box model.

2.2. Parametrization of Shading Device – Independent (Decision) Variables

Shading device's parameterization was conducted by using Grasshopper an algorithmic modelling platform. The geometry of the shading was generated by subdividing a surface that was 5 cm away from the south façade into six parts. This would allow controlling of the conceptual shading system with zones. Subsequently, each of these parts was subdivided again into 30 parts. These operations generated a data tree with six lists each having 30 items. Each of the surfaces would form horizontal slats of the shading devices with a dimension of 0.03 m ×1.49 m. An axial rotation operation was defined for all the surfaces in six different lists. Shading surfaces in separate lists were controlled by independent rotation parameters (X_1, …, X_6), which could have a value within the range of 0.00 to 180.00 degree. Recall that, the designs of shading devices were identical for both responsive kinetic and static types to facilitate fair comparison.

2.3. Inclusion of Performance Metrics to the Parametric Model

Inclusion of performance metrics to the parametric model was achieved using well-established plug-ins for Grasshopper. Ladybug and Honeybee are open source plug-ins for Grasshopper, developed for aiding the designers to explore and evaluate environmental performance of any design alternative at the conceptual design phases. With help of the programs within Ladybug toolset, it is possible to import EnergyPlus weather data files (EPW) into Grasshopper, make various environmental analyses that rely on previously recorded local time-series data. Honeybee toolset contains programs that connects visual programming environment of Grasshopper with various validated simulation engines such as EnergyPlus, Radiance, Daysim and

OpenStudio [18]. An integrated and flexible design approach can easily be utilized in the design process by means of those plug-ins and the visual scripting environment that Grasshopper platform provides. By generating a definition on Grasshopper various design variables and associative performance data can easily be generated for further research.

2.4. Database Generation

A performance integrated parametric model was generated for exploring the alternatives in the design space and the response variables of the static and responsive kinetic shading devices. The previously established parametric model had six independent variables, and three response variables (objectives) that are referred to as performance metrics. The next step was automating the process of generating and recording random independent variables for the control of shading zones and their computed performance metrics in a database. To achieve this goal 6-steps procedure had to be fulfilled.

- Step 1: Generate 6 random values within the range for shading control parameters (independent variables).
- Step 2: Run daylight, energy and view simulations for each the generated scenarios.
- Step 3: Write shading independent design variables and dependent response variables to spreadsheets.
- Step 4: Iterate the above process for 500 times for each hour.
- Step 5: Change the hours of the year.
- Step 6: Iterate for 50 times.

Nabil and Mardaljevic [19] argued that sub-sampling the meteorological dataset, such as picking only one day from each month, eventually bring biases because different sky and conditions would be excluded. However, in the research presented here, the aim is not making an annual inference, but examining the point in time situation. For this reason, a random sampling of 50 hours was made from total daylight hours of a year, provided that the selected hours were between 9:00 am and 17:00 pm.

Simulations were run on an hourly basis for the randomly sampled times in a year. By assigning random values for the decision variables within the range, 500 simulations were performed for each of the 50 randomly sampled hours. For the static shading, a randomly generated set that contains 500 examples were performed on an annual basis. Therefore, aggregated 25.500 runs were performed in an automated workflow to generate 51 datasets for further development of surrogate models. At each run, the independent variables and their associative variables that contain performance indicator values for each hour and a year were stored in separate spreadsheets. After finishing the database generation procedure, each spreadsheet was converted to comma-separated values (CSV).

2.5. Development of Surrogate Models

In the experimental design of the current study, development of surrogate models played a central role since they served two crucial purposes:

1. First, they were employed as the objective functions for the subsequent optimization process. Since they established the causal relationship among input and output variables, the current work utilized these relationships towards concurrent evaluation of the performance metrics.
2. Second, they functioned as the performance metric predictor of the static shading devices on considered date/hour of the year to facilitate comparative results with the performance results obtained for RKSD.

Feed-forward Artificial Neural Networks (FAAN) was used for development of surrogate models. In feed-forward neural networks, a connection is allowed only from a node in a layer to nodes in the next forward layer. Multi-layer feed-forward networks are very popular and long-established structures of artificial neural networks, which have been used in many applications such as forecasting and function approximation [20]. This class of neural networks is identified by presence of hidden layers between the input and output of the network. Hidden layer contains hidden neurons, which are not directly seen from either input or output [21]. The models that were prepared for the study are in the class of multilayer perceptron (MLP), since they have one hidden layer, other than just having an input and output layer. According to the extensive review conducted by Zhang, Patuwo, and Hu [20] ANN with a single hidden layer are sufficient to approximate any complex non-linear function at any degree of accuracy. Therefore, number of hidden layers was not a parameter to search for in the model selection process that was conducted for finding best performing network models and avoiding over-training of the networks.

Prior to generating MLP, three model selection operations were executed for each performance metrics to determine the network architectures. For network architectures that would be used for RKSD models, a dataset from a random hour was selected for testing network model, other than performing it to all the 50 datasets. The network architecture that outperformed remainders for the selected hour was then used for 49 remainder hours for RKSD. For annually optimized static shading, this was not an issue because the network models used one dataset for annual performance.

For cross validation, Monte Carlo technique was implemented for both model selection and neural network training processes. Using Monte-Carlo, the randomly generated data sample was split into two random sub-samples by a factor of 0.1. That is, 450 random observations (corresponds to 0.9) in the datasets were used for neural network training purposes. To assess predictive ability of trained network on the unseen data, remaining 50 observations, namely test sample was used. This process was then iterated 10 times, generating new training and test partitions at random each time. The performance evaluation criteria for cross-validation is root mean square error (RMSE) [1] which is subject to minimization.

Once the network architectures and number of iterations were determined for the models, the networks were trained using the data that contain simulation-derived observations. MLPs were trained by Resilient Back-Propagation (RProp) algorithm. RProp is a fast learning algorithm for MLPs that performs local adaptation of the weight-updates due to the act of the error function. Detailed information on training algorithm used in the current study can be found elsewhere [22]. Developed by Chatzikonstantinou [23], CIDEA, a Computational Intelligence Decision-Support Environment for Architectural and Building Design was used to conduct the tasks of surrogate model development and multi-objective optimization.

2.6. Multi-Objective Optimization – Objective functions

HypE algorithm was employed for deriving optimal solutions with respect to $|\Delta T|$, $|\Delta lux|$, and

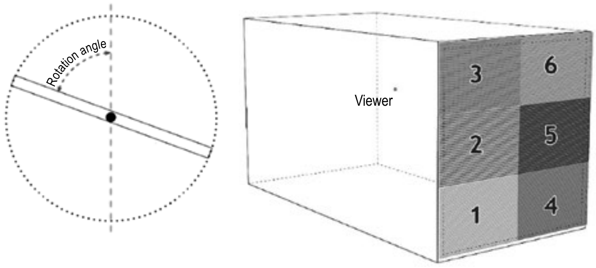

Fig. 2. Exterior shading system with six control zones and the diagram of a single shading control parameter

View. Bader, et. al. [24] proposed *HypE* as an evolutionary multi-objective optimization algorithm that is based on quality measure of hyper-volume indicator. In their study, they compared the algorithm with other evolutionary optimization algorithms such as *NSGA-II, SPEA2* and so on. Their results showed that *HypE* outperformed all the others, in multi-objective optimization problems with a dimension more than two. Therefore, *HypE* algorithm seems adequate for three-dimensional optimization problem that was formulated for the study of exterior shading devices.

According to the problem formulation, while $|\Delta T|$ and $|\Delta lux|$ objectives were minimized, *View* was maximized. This formed an obvious conflicting situation. In the optimization phase, *HypE* algorithm was referenced to the neural networks for each objective function.

The current work used the default settings for optimization to generate 100 generations each having 100 populations, whereas hyper-volume samples and mutation probability was set as 5000, and 0.1, respectively. Surrogate-based optimization method was implemented for both types of conceptual shading devices to reach the best performing design alternatives. For RKSD50 optimization operations were run for each randomly sampled daylight hours. For the static shading, only one optimization operation was performed to find best performing alternatives on an annual basis. At the end of the process, we extracted 100th generation from each of the 51 optimization processes in total, for further operations.

2.7. Test of Hypotheses

The current work hypothesized that responsive-kinetic shading device would outperform optimized-static selected performance criteria. Accordingly, following alternative hypotheses were tested:

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1 $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2}$.

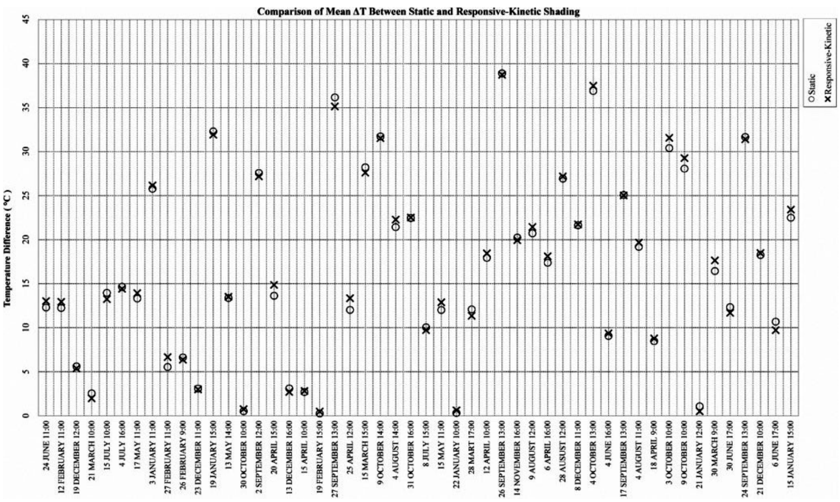

Fig. 3. Comparison of mean $|\Delta T|$ between static and RKSD

- $H_{alt,1} = \left|\Delta T_{responsive}\right| - \left|\Delta T_{static}\right| \le 0$;
- $H_{alt,2} = \left|\Delta lux_{responsive}\right| - \left|\Delta lux_{static}\right| \le 0$;
- $H_{alt,3} = View_{responsive} - View_{static} \ge 0$.

The design of experiment dictates to compare the means of one sample having different interventions whereas the data is in continuous domain. The same set of items was measured under two different interventions, namely responsive-kinetic and optimized-static. Therefore, paired-*t* test is the adequate statistics to conduct formal test of hypothesis.

3. RESULTS AND DISCUSSION

Upon successful implementation of the experimental design, exhaustively explained in the previous section, the current work obtained 50 sets of optimized decision variables for 50 randomly selected daylight hours for the responsive shading and one set of optimized decision variables for the static shading. Each of the 51 data sets is consisted of 100 optimized design alternatives.

Prior to implementing surrogate-based optimization, several pilot studies were conducted by using simulation-based optimization method of RKSD on arbitrarily selected daylight hours. The main intent of these studies was to verify the design of experiment as well as to calculate necessary duration of reaching near optimum solutions when using simulation-based technique. In pilot studies, near-optimum solutions for just a single hour in a year emerged only after a process that lasted for more than 60 hours. That is, when an architect chose to implement traditional simulation-based optimization technique towards performance evaluation of RKSD on, say, 50 selected hours of a year, he/she requires approximately 125 days achieving that task. On the other hand, utilizing surrogate models reduced the computational costs significantly. The investigation of the performance for the RKSD, on 50 randomly sampled daylight hours lasted for about 90 hours in total; whereas the computer conducted most of the process in an automated fashion.

Three hypotheses were considered within the content of the current study. In each, it was assumed that the responsive-kinetic shading type would outperform the optimized static one. However, the results of paired-*t* tests significantly demonstrated that, while $H_{alt,2}$ and $H_{alt,3}$ cannot be rejected $H_{alt,1}$ can be rejected. This implies, while responsive kinetic shading outperformed optimized static with respect to daylight intensity and view to outside, there was no significant difference in the comparison of the impacts of the two types of shadings on indoor air temperature.

The first objective function was $|\Delta T|$ minimization. Therefore, we expected lower $|\Delta T|$ values for responsive-kinetic shading type. However, the results suggest there is not enough evidence to conclude that the mean of responsive-kinetic shading is less than static shading at the 0.05 level of significance. We found out that the mean of $\left|\Delta T_{responsive}\right|$ is 16.77 °C, while the mean of $\left|\Delta T_{static}\right|$ is 16.60 °C.

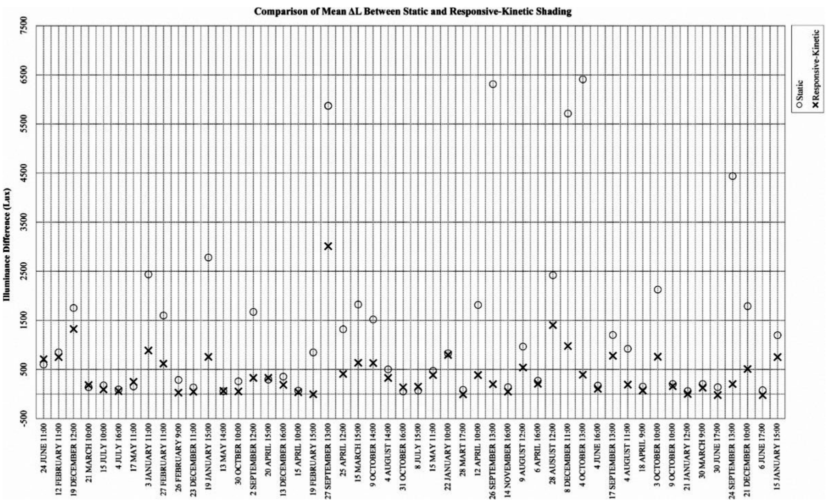

Fig. 4. Comparison of mean $|\Delta lux|$ between static and RKSD

In an indoor space with a solely southern-exposure to the sun in Izmir climate, responsive-shading devices may not contribute to thermal comfort and energy efficiency better than an optimized static shading device. To further underline, the study considered other objective functions in the optimization problem simultaneously. The function of view to outside maximization might have influenced this result, since it is an obviously conflicting objective in most of the weather conditions. Fig. 3 illustrates paired comparison of mean $|\Delta T|$ on randomly selected hours.

The second performance objective function was minimization of $|\Delta lux|$. As in the first objective, the current work aimed at minimizing $|\Delta lux|$ to make the average daylight intensity as close to 500 lx as possible. In the comparison test for $|\Delta lux|$ objective, the findings of the current study suggest that the RKSD performs significantly better than optimized the static shading at the 0.05 level of significance. The results revealed that the mean of $|\Delta lux_{responsive}|$ is 420 lx, while the mean of $|\Delta lux_{static}|$ is 1277 lx. The daylight performance of responsive-kinetic shading is almost three times better than the optimized static shading according to the findings. However, it must be noticed that five of the paired differences were unusual, that is the difference between the pair is much more than the trend, Fig. 4.

This situation contributed to the increase in the total mean difference. Nonetheless, one can be 95 % confident that the true mean difference is less than 507 lx and 90 % percent confident that it is between 507 and 1206 lx.

The final objective function for the performance evaluation was percentage of view to outside (*View*). Maximization was intended for this function, therefore higher values of $View$ is desired. The findings suggest that the mean of $View_{responsive}$ and $View_{static}$ is 64.2 and 48.4, respectively. As reported in the results, we can conclude that the mean of responsive-kinetic shading is significantly greater than the mean of optimized static shading at the 0.05 level of significance. We can be 95 % confident that true mean difference is greater than 12.7, and 90 % confident that it is between 12.7 and 18.7. Fig. 5 illustrates paired comparison of *View* objective.

The reason for these results may be related with the formulation of the experiment. The controlled experiment was designed for the investigation of sole impact of sunlight on the interior environment. The solar beams have two diverse but related aspects, namely thermal and daylight. Heat energy cannot reflect but radiate. Both shading devices intercepted the heat energy of solar beams on the outside in a similar manner. However, daylight aspect of solar beams was managed much better by responsive kinetic shading type. Objective performance about window view in the design problem statement, which is not a dynamic measure, conflicts with the other objectives, and might has be contributed to this situation.

CONCLUSION

The current work established a novel framework for adequately exploring design alternatives and optimizing performance of control parameters of responsive-kinetic shading devices with respect to objectives of $|\Delta T|, |\Delta lux|$ $View$. The urge for

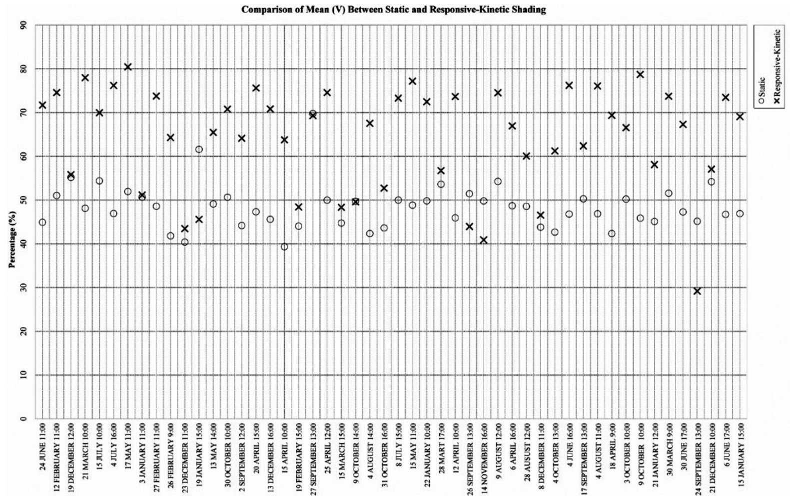

Fig. 5. Comparison of mean *View* between static and RKSD

developing such framework was motivated by the absence of an adequate and efficient method for exploring and evaluating the performance of RKSD. In addition, literature has not addressed the task with consideration of thermal, daylight, and view objectives simultaneously up to now. Findings suggest one can achieve significant reduction in computational time compared to simulation-based methods using proposed framework. A surprising outcome was the optimized static shading slightly outperformed the responsive-kinetic one in the objective $|\Delta T|$. Considering the objectives $|\Delta lux|$ and $View$, however, empirical evidences suggested that RKSD significantly outperformed the optimized-static shading.

In the future works, the relationships between weather conditions, design variables and performance objectives should further be examined. Certain weather parameters, such as global illuminance, global radiation, are required to be extracted from the weather file and match with the design and response parameters to picture the relationships between them.

REFERENCES

1. G. Hausladen, M. de Saldanha, and P. Liedl, *Climate Skin*. Basel: Birkhauser, 2008.
2. H. Fathy, *Natural Energy and Vernacular Architecture*. Chicago and London: The University of Chicago Press, 1986.
3. A. Olgyay and V. Olgyay, *Solar Control and Shading Devices*. New Jersey, 1977.
4. N. Lechner, *Sustainable Design Methods for Architects*. New Jersey: Wiley, 2015.
5. C. Du Montier, A. Potvin, and C.M. Demers, "Energy and daylighting potential for Adaptive Façades: Evaluation of movable insulated panels," Proc. of Int. Conf. on Adaptation and Movement in Architecture ICAMA 2013, Oct. 2013, Toronto, Canada.
6. Y.J. Grobman, I.G. Capeluto, and G. Austern, "External shading in buildings: comparative analysis of daylighting performance in static and kinetic operation scenarios," *Architectural Science Review*, 2016, Vol. **60**, no. **2**, pp. 1–11.
7. K. Kensek and R. Hansanuwat, "Environment Control Systems for Sustainable Design: A Methodology for Testing, Simulating and Comparing Kinetic Facade Systems," *Journal of Creative Sustainable Architecture & Built Environment*, 2011, Vol. 1, no. Nov., pp. 27–46.
8. D. S. Lee, S.H. Koo, Y.B. Seong, and J.H. Jo, "Evaluating thermal and lighting energy performance of shading devices on kinetic façades," *Sustainability (Switzerland)*, 2016, Vol. 8, no. 9, pp. 1–18.
9. M. V. Nielsen, S. Svendsen, and L.B. Jensen, "Quantifying the potential of automated dynamic solar shading in office buildings through integrated simulations of energy and daylight," *Solar Energy*, 2011, Vol. 85, no. 5, pp. 757–768.
10. M. El Sheikh and D.J. Gerber, "Building Skin Intelligence," *Proceedings of the annual conference of the Association of Computer Aided Design in Architecture ACADIA*, 2011, pp. 170–177.
11. K. Sharaidin, J. Burry, and F. Salim, "Integration of Digital Simulation Tools With Parametric Designs to Evaluate Kinetic Façades for Daylight Performance," *Physical Digitality: Proceedings of the 30th eCAADe Conference,* 2012, Vol. 2, pp. 701–709.
12. T. Wortmann, A. Costa, G. Nannicini, and T. Schroepfer, "Advantages of surrogate models for ar-

chitectural design optimization," *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, 2015, Vol. 29, no. 4, pp. 471–481.

13. T. Kazanasmaz, M. Günaydin, and S. Binol, "Artificial neural networks to predict daylight illuminance in office buildings," *Building and Environment*, 2009, Vol. 44, no. 8, pp. 1751–1757.

14. J. Hu and S. Olbina, "Illuminance-based slat angle selection model for automated control of split blinds," *Building and Environment*, 2011, Vol. 46, no. 3, pp. 786–796.

15. M. E. Skavara, "Adaptive cellular automata façade trained by artificial neural network," Barlett School of Graduate Studies, University Collage of London, 2009.

16. E. S. Lee, D.L. DiBartolomeo, and S.E. Selkowitz, "Thermal and daylighting performance of an automated venetian blind and lighting system in a full-scale private office," *Energy and Buildings*, 1998, Vol. 29, no. 1, pp. 47–63.

17. A. Wagdy, F. Fathy, and S. Altomonte, "Evaluating the Daylighting Performance of Dynamic Façades by Using New Annual Climate- Based Metrics Evaluating the Daylighting Performance of Dynamic Façades by Using New Annual Climate – Based Metrics," Proc. of the 32nd Int. Conf. on Passive and Low Energy Architecture, PLEA 2016. 2016, Los Angeles, CA, pp. 941–947.

18. M. Sadeghipour Roudsari and M. Pak, "Ladybug: a Parametric Environmental Plugin for Grasshopper To Help Designers Create an Environmentally-Conscious Design," *13th Conference of International building Performance Simulation Association*, 2013, pp. 3129–3135.

19. A. Nabil and J. Mardaljevic, "Useful daylight illuminance: a new paradigm for assessing daylight in buildings," *Lighting Research and Technology*, 2005, Vol. 37, no. 1, pp. 41–59.

20. G. Zhang, B.E. Patuwo, and M.Y. Hu, "Forecasting with artificial neural networks:: The state of the art," *International journal of forecasting*, 1998, Vol. 14, pp. 35–62.

21. S. Haykin, *Neural Networks and Learning Machines*. 2009.

22. M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: The RPROP algorithm," *IEEE International Conference on Neural Networks – Conference Proceedings*, Vol. 1993–Janua, pp. 586–591.

23. I. Chatzikonstantinou, "A Computational Intelligence Decision-Support Environment for Architectural and Building Design: CIDEA," *IEEE Congress on Evolutionary Computation 2016*, pp. 3887–3894.

24. Bader, J., Zitzler, E. HypE: An Algorithm for Fast Hypervolume-Based Many-Objective Optimization // Evolutionary Computation. 2008, Vol. 19, No. 1, pp. 45–76.

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