

VIRTUAL TOXICITY STUDIES OF NOVEL SPIROAZETIDIN-2-ONE STETHERED WITH FURANS

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ABSTRACT:

Common uses for spiroazetidin-2-ones and furans include anti-inflammatory, anti-fungal, anti-cancer, anti-parkinson, and cardiovascular effects. The researchers in this investigation set out to simulate toxicity tests on the synthetic chemicals 1-(substitutedphenyl)-3-chloro-5,9-bis(furan-2-ylmethylidene)-1a-3h-alkyl azaspiro[3.5]nonan-2-ones list is long. Subjects and procedures: The TOPKAT 6.1 (Toxicity Prediction Komputer Assisted Technology version 6.1) was used to develop computational toxicology and mutagenicity profiles of these substances. After receiving the query molecule's molecular structure as a SMILES string and choosing a TOPKAT predictor, TOPKAT automatically analyses

the compound. The results show that chemicals 3a-3h do not undergo aerobic biodegradation and do not cause mutations, as predicted by the TOPKAT 6.1 model. Oral LD50 values for compounds 3a-3h in rats were estimated to be between 1.1 and 115.0 mg/kg. The chemicals seem to be more safe due to their high LD50 values. For all substances, the calculated likelihood of skin irritation was 1.000, and for carcinogenicity, it was determined to be 0.950-1.000. The use of computerized statistical methods allows for the identification of more promising compounds. Based on the results of these investigations, we set out to determine the toxicological profile of new spiroazetidin-2-one bound with furan moieties.

Keywords: Spiroazetidin-2-one, Furan, Toxicity, Mutagenicity, TOPKAT

INTRODUCTION: Spiroazetidin-2-

ones and furans have emerged as an important class of drugs for the treatment of a variety of health conditions. The compounds having these nuclei are commonly used to treat health conditions which include anti-bacterial, anti-fungal, anti-inflammatory, cardiovascular anticancer, anti-parkinson agents *etc.*¹⁻⁷.

Drug design software like TOPKAT enable the discovery of lead molecules, more efficiently and quickly. Conventional synthesis and evaluation of drugs require number of animal sacrifices, use of this software helps in reducing the number of animal sacrifices made for the *in vivo* studies. TOPKAT accurately and rapidly assess the toxicity of drugs solely from their 2D molecular structure using a range of robust, cross-validated Quantitative Structure Toxicity Relationship (QSTR) models for assessing specific toxicological end points, thus providing a detailed data of query molecules which can be widely analyzed and

compared with the existing molecular libraries. Use of QSAR software undoubtedly reduces the number of compounds synthesized thereby providing with promising leads for further exploration. The rationale behind this work was to develop extensive toxicological profile of the derivatives containing 1-(substitutedphenyl)-3-chloro-5,9-bis(furan-2-ylmethylidene)-1-azaspiro[3.5]nonan-2-ones (3a-3h)⁸.

MATERIALS AND METHODS: The molecular structure of the query compound is given as SMILES string and a desired TOPKAT predictor is selected. If the structure is a member of training set, the database information for the compound is displayed. If the query does not belong to the training set, software displays the result with necessary warnings. Under these circumstances, caution in accepting the estimates should be exercised. Models which satisfy all the validation criteria for the query compound are computed and results are recorded⁹.

Virtual toxicity studies have been done for the following set of compounds, substitutions for which is given in **Table 1**.

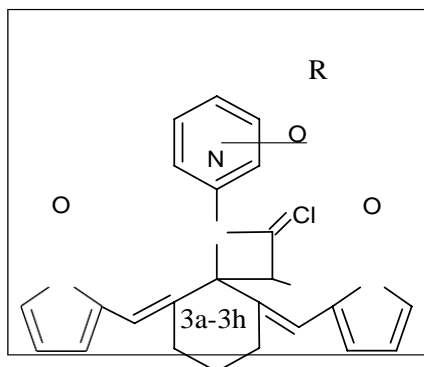


TABLE 1: SET OF COMPOUNDS FOR SCREENING

Compound	R
3a	H
3b	4-NO ₂
3c	4-Cl
3d	4-Br
3e	2-NO ₂
3f	3,4-diCl
3g	4-F
3h	2,6-diCl

Evaluating an assessment: If we consider a TOPKAT assessment of a query structure as a hypothesis which states that the model parameters present in the query structure are the determinants of its toxicity, then this hypothesis can be tested against similar compounds in the model's database. The similarity search function in TOPKAT will automatically rank all the compounds in the respective model database based on their QSTR similarity to the query structure. Information regarding the actual experimental result, TOPKAT predicted result and whether the compound was used in training set is available for each compound. With this information whether the query structure lies in an information-rich region of the model dataspace and similar compounds are well predicted by the model is determined.

Computation of toxicity by TOPKAT:

TOPKAT computes a probable value of toxicity for a submitted chemical structure from a Quantitative Structure-Toxicity Relationship (QSTR) equation. The equation is linear in the structure descriptors. The coefficients are optimized during the development of the equation. The product of a structure descriptor's value and its corresponding coefficient is the descriptor's contribution to the probable

toxicity. Contributions from the products may be either positive or negative; a positive contribution will increase the probability of the chosen property, whereas a negative contribution will decrease it. Toxicity values are computed

by summing the individual contributions. For assessing toxicity values such as LD₅₀ or LC₅₀, this sum is transformed into a weight/weight unit (mg/kg) or a weight/volume unit (mg/l); for 2-group classifications, such as carcinogens/non-carcinogens, this sum is transformed into a probability value between 0.0 and 1.0.

Probability values: Probability values from 0.0 to 0.30 are considered low probabilities, and chemical swith TOPKAT-computed probability values in this range are not likely to produce a positive response in an experimental assay; whereas probability values greater than 0.70 are considered high, and are likely to produce a positive response in an experimental assay. Probabilities greater than 0.30 but less than 0.70 are considered indeterminate (i.e., too near chance (0.50) for an assessment to be meaningful).

Query structure Examination: TOPKAT always outputs a value of toxicity; however,

whether the assessment is meaningful or not can only be answered by:

1. A univariate analysis or Coverage Examination, that is, whether all of the structural fragments of the query structure are well represented in the database compounds which were used to develop the model (training set).
2. A multivariate analysis, or OPS Examination, that is, whether the submitted structure fits within, or near the periphery of, the Optimum Prediction Space (OPS) of the equation.

These 2 steps are accomplished automatically in TOPKAT and results are output in terms of a confidence percentage.

Coverage Examination: Every QSTR model is associated with a certain training set of compounds, and these compounds contain a limited set of structural attributes. A QSTR model, when extrapolated to chemical structures containing structural attributes which are not represented in the training set, may produce unreliable toxicity assessments. Therefore, it is important to determine whether the structural attributes of the query molecule are represented in the compounds used for the development of a QSTR. TOPKAT automatically determines whether the input structure contains molecular substructures which are foreign to the training set (a univariate analysis). Additionally, during this process, TOPKAT compares the values of the model descriptors for the query structure to the range of the values of the respective descriptors in the training set compounds.

RESULTS AND DISCUSSION: All the 8

derivatives containing 1-(substituted phenyl)-3-chloro-5,9-bis(furan-2-ylmethylidene)-1-azaspiro[3.5]nonan-2-ones (3a-3h) were extensively studied by TOPKAT 6.1.

Optimum prediction space: As well as determining its coverage, TOPKAT checks whether a query structure is located inside or outside the Optimum Prediction Space (OPS) of a QSTR (multivariate analysis). The OPS of a QSTR is a multidimensional space, the number of dimensions being one more than the number of model parameters of the QSTR.

An important characteristic of the OPS is that within and near its periphery the QSTR may be applied with confidence. The OPS confidence contains information about both the Optimum Prediction Space and the fragment coverage. When a query structure is determined to be inside all dimensions of a model OPS, the computed value of toxicity can be considered acceptable (unless evidence exists to refute the assessment).

However, if a query structure is found outside one or more dimensions, the computed toxicity may or may not be acceptable depending on the query's distance from OPS. The distance of a query structure from the OPS is a complex function of the query's location in each dimension. Every TOPKAT QSTR model has a permissible limit of distance from the OPS.

If the query structure's distance from the OPS is greater than this permissible limit, the TOPKAT-assigned toxicity value is considered unacceptable. The permissible limits of distance from the OPS for all QSTR models have been precalculated and stored in TOPKAT. For every query structure outside the OPS, TOPKAT reports the location of a query structure with respect to the permissible limit of distance from the OPS.

TABLE2:RATORALLD₅₀ANDLOGPDATA

Compound	RatOralLD ₅₀ (v3.1)		LogP(v3.1)	
	Computed RatOralLD ₅₀	95% Confidence Limits	Assessment ofLogP	95% Confidence Limits
3a	708.9mg/kg	110.7mg/kg&4.5g/kg	3.575	3.144&4.006
3b	386.6mg/kg	62.0mg/kg&2.4g/kg	2.641	2.209&3.074
3c	385.5mg/kg	61.9mg/kg&2.4g/kg	4.076	3.647&4.506
3d	330.4mg/kg	51.8mg/kg&2.1g/kg	4.249	3.818&4.680
3e	353.8mg/kg	57.4mg/kg&2.2g/kg	2.433	1.997&2.868
3f	115.0mg/kg	17.9 mg/kg&737.5mg/kg	4.467	4.035&4.900
3g	1.1g/kg	174.2mg/kg&6.8g/kg	3.406	2.977&3.835
3h	158.6mg/kg	25.4mg/kg&992.0mg/kg	4.103	3.658&4.548

TABLE3:AEROBICBIODEGRADABILITYANDDEVELOPMENTALTOXICITYPOTENTIALDATA

Compound	AerobicBiodegradability (v6.1)		DevelopmentalToxicityPotential(DTP)(v3.1)	
	ComputedProbability	DiscriminantScore	ComputedProbability	DiscriminantScore
3a	0.000	-32.704	0.000	-18.738
3b	0.000	-28.347	0.000	-20.378
3c	0.000	-41.558	0.000	-19.894
3d	0.000	-11.896	0.000	-19.894
3e	0.000	-35.526	0.000	-18.535
3f	0.000	-46.264	0.000	-15.177
3g	0.000	-50.663	0.000	-19.894
3h	0.000	-35.821	0.000	-12.636

TABLE4:MUTAGENICITYANDSKINIRRITATION DATA

Compound	Mutagenicity(v3.1)		SkinIrritation(v6.1)	
	Probability ofBiodegradability	DiscriminantScore	Probability ofMOD/SE V	DiscriminantScore
3a	0.000	-25.709	1.000	58.610
3b	0.000	-14.440	1.000	44.446
3c	0.000	-27.855	1.000	53.970
3d	0.000	-28.208	1.000	53.090
3e	0.000	-16.493	1.000	43.507
3f	0.000	-31.181	1.000	51.567
3g	0.000	-34.760	1.000	56.984
3h	0.000	-33.709	1.000	48.272

TABLE5:CARCINOGENICITYMALEMOUSEAND CARCINOGENICITYFEMALEMOUSEDATA

Compound	CarcinogenicityMaleMouse(v3.2)		CarcinogenicityFemaleMouse(v3.2)	
	ComputedProbability	DiscriminantScore	ComputedProbability	DiscriminantScore
3a	1.000	104.21	1.000	23.503
3b	1.000	118.636	1.000	29.191
3c	1.000	110.701	1.000	27.277
3d	1.000	109.731	1.000	24.590
3e	1.000	114.986	1.000	26.679
3f	1.000	112.927	1.000	21.776
3g	1.000	113.473	1.000	34.954
3h	1.000	107.591	1.000	24.806

TABLE6:CARCINOGENICITYMALERATANDCARCINOGENICITYFEMALERATDATA

Compound	CarcinogenicityMaleRat(v3.2)		CarcinogenicityFemaleRat(v3.2)	
	ComputedProbab ility	DiscriminantScor e	ComputedProba bility	DiscriminantScor e
3a	0.969	3.452	0.058	-25.709
3b	0.998	6.464	1.000	-14.440

3c	0.980	3.911	0.000	-27.855
3d	0.980	3.911	0.000	-28.208
3e	0.999	6.505	0.924	-16.493
3f	0.987	4.351	0.000	-31.181
3g	0.980	3.911	0.000	-34.760
3h	0.986	4.257	0.000	-33.709

According to TOPKAT 6.1 model, the computed Ratoral LD50 values for the compounds 3a

3h ranged from 1.1 g/kg to 115.0 mg/kg. These high LD₅₀ values suggest higher safety of these compounds. And Log P values of all 8 derivatives are well below 5.6. So Log P parameter of all the derivatives obey Lipinski's rule and fall well within the range of -0.4 to +5.6 (**Table 2**).

The compounds (3a-3h) were devoid of aerobic biodegradability. The structure descriptors contribute negatively to the assessment of confidence limits. All the derivatives result in very low computed probability and negative discriminant score values for Developmental Toxicity Potential (V 3.1). Data is given in **Table 3**.

All the 8 compounds (3a-3h) are non-mutagenic and the computed probability of skin irritation for all compounds was found to be 1.000, there would be probability of skin irritation on topical application (**Table 4**).

All the derivatives showed the computed probability value

1.0 and discriminant scores are not likely to produce a positive response in an experimental assay and positive contribution to the increase in the probability of chosen property which is carcinogenicity of male mouse (V 3.2) and female mouse (3.2). Data is given in **Table 5**. Computed probability values of all the derivatives range from 0.96 to 0.99 for the carcinogenicity of male rat (V 3.2) are greater than 0.7, which implies that they are likely to produce a positive response in an experimental assay.

All the derivatives except 3b and 3e showed the computed probability value less than 0.7 and negative discriminant scores are not likely to produce a positive response in an experimental assay and negative contribution to the increase in the probability of chosen property which is carcinogenicity

of female rat (V 3.2). Data is given in **Table 6**.

CONCLUSION: The success of previous generation of drugs and vaccines has led to an increase in human life expectations. But it does not mean that all the molecules developed each year by random screening methodology are successful to provide new blockbuster drugs. So it is time to change the methodology for research from random screening to rationalized approach of drug design. By following the computerized statistical methodology, more promising molecules can be identified. This has provided us with some direction for research to carry out an extensive study of novel derivatives of Spiroazetidin-2-one tethered with furans (3a-3h) for their toxicological profile.

REFERENCES:

- One, Srivastava SD, Pushkal S, Sharma R, and Srivastava SK. Phenothiazine 2-oxo-azetidine derivatives: synthesis and biological action. The organic communication was published in 2011 with the number 43.
2. Karanj Parikh, Parikh AR, Oza PS, Bhatt SB. Possible antitubercular drugs derived from a novel class of 2-azetidinones synthesized. Publication: 2000 in the Indian Journal of Chemistry, Section B: Organic Chemistry, Incorporated Medical Chemistry, 39, 716-718.
3. Shaheed M. Sreenivasa, Jayachandran E., Yognanda R.
4. H. New N-substituted-3-chloro-2-azetidinones: synthesis and characterisation for anticonvulsant drug development. [Published in 2009] in the Journal of Biomedical Science and Research.
5. Four authors: Singh, Sharma, Srivastava, and Kumar. A few substituted pyridine derivatives: synthesis and insecticidal actions. Journal of Organic Chemistry, Part B: Industrial and Medical Chemistry, 2006, 45: 1557-1563.
6. Kumar S, Kaur H, and Kumar K. *Kumari, Saxena, Sharma, and Vishwakarma *P. Novel adamantylthiazolidinonyl/azetidinonylindole derivatives: synthesis and antiparkinsonian efficacy. Article published in 2010 in the Indian Journal of

- Chemistry, Section B: Organic Chemistry, Including Medical Chemistry, 49: 1398–1405.
7. 6. The authors are Goel RK, Mahajan MP, and Kulkarni SK. Several new monocyclic beta lactams were tested for their ability to prevent hyperglycemia. *Proceedings of the Journal of Pharmaceutical Science*, 2004; 7: 80-3.
 8. Kumar HK, Banerjee M., and Banerjee R. Medicinal importance of furan derivatives: A Review. *Global Journal of Life Sciences*. 2012; 2: 7-16.
 9. Rajikala R, Babu MN, 8. New Spiroazetidin-2-ones attached to furans: synthesis and characterization for antimicrobial and anti-inflammatory purposes. Published in 2017 in the *World Journal of Pharmaceutical Research*, volume 6, pages 681–690.
 11. Virtual toxicity investigations of new 1,4-dihydropyridine compounds. Asma SA, Venkataramana CHS, Madhavan V., etc. "International Research Journal of Pharmaceuticals" (2013), 4, 249–255.
 12. This is the tenth publication by Swain, Samanthula, Bhagat, Bharatam, PV, Akula, and Sinha. Sofosbuvir: A new inhibitor of the human hepatitis C virus NS5B polymerase and its forced degradation products; in silico toxicity prediction. The citation for this article is *Jan Pharm Biomed Anal* 2016: 120: 352-63.
 13. 11. Ismail IS, Wai LK, and Radhakrishnan Narayanaswamy AI. Investigation of some compounds in *Clinacanthus nutans* using molecular docking as inhibitors of xanthine oxidase, nitric oxide synthase, human neutrophil elastase, matrix metalloproteinase 2, matrix metalloproteinase 9, and squalene synthase. *Pharmaceutical Magazine*, 2016; 12: S21.
 14. 12. The authors are Manral, Saini, Meena, and Tiwari. New diallyl disulfide (DADS) compounds that have several functions, including decreasing β -amyloid, acting as cholinergic agents, acting as antioxidants, and chelating metals, are being developed for the treatment of Alzheimer's disease. The article was published in *Bioorg Med Chem* in 2015 and can be found on page 6394-003.
 16. 13. The authors of the study are GonellaDiasa, Manganelli, Esposito, Roncaglioni, Manganaro, and Benfenati. 7. We compare in silico methods for assessing acute toxicity in rats when given oral poisoning. *Environmental Research (SAR QSAR)* 2015; 26: 1-27.
 17. 14. A Singh, Srivastava R, and RK Singh. Innovative Heterocyclic Arylsulphonamide Derivatives: Design, Synthesis, and Antimicrobial Activities. *Overarching Subject Sci: Comput Life Sci*. 2017; 13: 1-4. 15. Srikala R, Babu MN. Adverse event and toxicity evaluation of new spiroazetidin-2-ones attached to furans. Screening of newly synthesized spiroazetidin-2-ones for oral action. In *World Journal of Pharmaceutical Sciences*, 2017; 6: 1351-7. 16. Srikala R, Babu MN. Published in 2017 in the *World Journal of Pharmaceutical Research*, volume 6, pages 995–999.